ABDEMOCRATIC AND POPULAR REPUBLIC OF ALGERIA

MINISTRY OF HIGHER EDUCATION AND SCIENTIFIC RESEARCH

ECOLE SUPÉRIEURE DE COMMERCE

End-of-cycle dissertation for the purpose of obtaining a Master's Degree in Financial Sciences and Accounting

Major: Corporate Finance

Topic:

Forecasting central bank Liquidity in Algeria:

A Comparative Analysis of statistical and Deep Learning Models

Submitted by:

Ms. BENKREDDA Charaf

Supervisor:

Dr. TAOUSSI Brahim

Co-Supervisor:

Pr. BENILLES Billel

Location of the internship: Bank of Algeria

Duration of the internship: From 15/02/2024 to 15/05/2024

Academic year: 2024/2025

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DEDICATION

To my beloved mama

For your boundless love, quiet strength, and unspoken sacrifices.
Your constant prayers and unwavering faith in me have shaped the person I am today.
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List of Abbreviations

Abbreviation	Signification
ADF test	Augmented Dickey-Fuller test
AI	Artificiel Intelligent
ALP	Autonomous Liquidity Position
ALP	Autonomous Liquidity Position
ARIMA	AutoRegressive Integrated Moving Average
BoA	Bank of Algeria
BR	Bank Reserves
CB	Central Bank
CBWAS	Central Bank of West African States
CIC	Currency In Circulation
CNN	Convolutional Neural Network
DL	Deep learning
EBC	The European Central Bank
KPSS test	Kwiatkowski–Phillips–Schmidt–Shin test
LM	Liquidity Management
LSTM	Long Short-Term Memory
NFA	Net Foreign Assets
NGP	Net Government Position
OMO	Open Market Operation
PP test	Phillips-Perron test
QE	Quantitative Easing
RNN	Recurrent Neural Network
RR	Required Reserve
RRF	Revenue Regulation Fund
RX	EXcess Reserves (RX)
SL	Supply of Liquidity
GoF	Goodness of Fit

Abstract

This study evaluates the forecasting performance of traditional time series models (ARIMA, VAR) alongside advanced deep learning methods (LSTM, CNN) in predicting key determinants of banking liquidity in Algeria. The analysis is based on daily data from 2015 to 2023, provided by the Bank of Algeria, focusing on three critical variables: Net Foreign Assets, Currency in Circulation, and Government Net Position. We first performed forecasting using the all-at-once method on the statistical models, then implemented a Rolling Forecast approach to enhance their predictive accuracy and adaptability over time. Following this, we proceeded to forecast using deep learning models to compare their performance with the statistical methods. Our results demonstrate that LSTM outperforms classical models in capturing complex nonlinear patterns and temporal dependencies in Net Foreign Assets and Government Net Position, while traditional models still provide reliable forecasts for Currency in Circulation, particularly when enhanced by Rolling Forecasts. This comparative analysis provides valuable insights for developing more effective forecasting tools to assist monetary authorities in improving liquidity management and maintaining the financial stability of Algeria.

Keywords: Banking liquidity, Bank of Algeria, Classical time series, LSTM, CNN.

الملخص

تقوم هذه الدراسة بتقييم أداء التنبؤ لنماذج السلاسل الزمنية التقليدية (VAR, ARIMA) إلى جانب طرق التعلم العميق المتقدمة (CNN,LSTM) في التنبؤ بالعوامل الرئيسية المؤثرة على السيولة البنكية في الجزائر. وتعتمد التحليلات على بيانات يومية للفترة من 2015 إلى 2023، مقدمة من بنك الجزائر، مع التركيز على ثلاثة متغيرات حاسمة هي: الأصول الخارجية الصافية، والعملة المتداولة، والمركز الصافي للحكومة.في البداية، قمنا بالتنبؤ باستخدام طريقة التنبؤ الجماعي (all-at-once) على النماذج الإحصائية، ثم طبقنا منهجية التنبؤ المتداول (Rolling Forecast) لتحسين دقة النماذج وقدرتها على التكيف مع التغيرات الزمنية. بعد ذلك، أجرينا التنبؤ باستخدام نماذج التعلم العميق لمقارنة أدائها مع النماذج الإحصائية . تُظهر نتائجنا أن نموذج LSTM يتفوق على النماذج التقليدية في التقاط الأنماط المعقدة وغير الخطية والاعتمادات الزمنية في الأصول الخارجية الصافية والمركز الصافي للحكومة، في حين تظل النماذج التقليدية توفر تنبؤات موثوقة للمتغير "العملة المتداولة"، خاصة عند تحسينها باستخدام طريقة التنبؤ المتداول. يوفر هذا التحليل المقارن رؤى قيمة لتطوير أدوات تنبؤية أكثر فعالية تساعد السلطات النقدية في تحسين إدارة السيولة والحفاظ على الاستقرار المالي في الجزائر.

الكلمات المفتاحية :السيولة البنكية، بنك الجزائر، السلاسل الزمنية التقليدية، LSTM، CNN.

General Introduction

Liquidity plays a crucial role in the stability of the financial system, influencing not only the health of banks but also the overall resilience of the economy. Disruptions in liquidity can lead to significant consequences, such as market turbulence, loss of confidence, and even a systemic crisis. Central banks, as key players in the financial system, are tasked with ensuring adequate liquidity while preventing excess, to maintain the proper functioning of markets and the broader economy. However, understanding and managing liquidity is complex, influenced by a combination of factors, including market expectations, economic cycles, regulatory changes, geopolitical events and the evolving behavior of financial institutions.

The balance between liquidity management and monetary policy is crucial, with central banks needing to address the immediate needs of the financial sector while maintaining a long-term view of economic stability. Decisions about liquidity provision, through market operations or reserve management, have widespread effects across the financial system. When calibrated correctly, these interventions help stabilize short-term interest rates, ensure smooth payment systems and support the transmission of monetary policy. On the other hand, poor judgment can increase market volatility, disrupt credit flows and undermine confidence.

In recent years, forecasting liquidity has become increasingly challenging. Financial innovation has introduced significant changes. Moreover, changes in regulations since the global financial crisis have reshaped bank's liquidity management. As a result, liquidity is increasingly affected by global dynamics and evolving regulatory frameworks. These transformations highlight the need to revisit traditional forecasting practices in light of evolving financial complexities.

While central banks have traditionally relied on established forecasting models such as ARIMA and VAR, these tools remain the cornerstone of liquidity forecasting and macroeconomic projections. Despite recent advances in artificial intelligence (AI), its integration into central bank decision-making processes remains limited. Classical models continue to dominate due to their interpretability, transparency, and long-standing use in institutional frameworks.

Research on liquidity forecasting using AI is still emerging, with most existing studies relying on classical methods, Soleimani (2024) highlights the potential of AI to improve forecasting and liquidity management. Our study contributes to this growing field by empirically evaluating both classical and AI-based models across multiple liquidity factors, offering a broader perspective on forecasting approaches.

The liquidity problem has become a growing concern in both developed and developing countries, and the concept of liquidity is now more critical than ever. In Algeria, there is a pressing need for a forecasting system capable of anticipating liquidity risks. Such a system would help safeguard the financial health of Algerian banks by allowing timely interventions and more effective monetary and regulatory decisions.

This study aims to highlight the potential benefits of AI in improving liquidity forecasting, ultimately contributing to greater economic stability. This approach could enable central banks to enhance their decision-making processes by more accurately anticipating liquidity needs, detecting emerging pressures, and adjusting interventions with greater precision.

The purpose of this research is to determine which methods are more effective in forecasting the liquidity of the Bank of Algeria. In this context, the research problem can be formulated as follows:

« How can deep learning models improve the accuracy of central bank liquidity forecasting compared to statistical models? »

The research problem raises several important sub-problems regarding the interaction between these financial variables and their impact on liquidity. To obtain an adequate answer to this problem, it is essential to consider the following secondary questions:

- Are net foreign assets, currency in circulation and net government position sufficiently relevant to predict central bank liquidity, or should other variables be taken into account?
- Are statistical time series models, such as ARIMA and VAR, more effective than deep learning techniques (CNN and LSTM) in capturing trends in bank liquidity in Algeria?
- Does the complexity of each liquidity factor influence the performance of forecasting models, and can this explain the varying effectiveness of classical and deep learning methods?

To address the issue, the possible answers are based on the following assumptions:

- **H1:** Net Foreign Assets, Currency in Circulation, and Net Government Position are sufficient to forecast central bank liquidity in Algeria
- **H2:** Statistical time series models, such as ARIMA and VAR, may be limited in their ability to accurately predict bank liquidity compared to deep learning models,
- **H3:** The effectiveness of forecasting methods depends on the complexity of the liquidity factor being predicted

The importance of this research lies in the fact that forecasting techniques and the application of AI in the context of Algeria are limited and relatively recent. A study addressing these aspects together could lead to entirely new findings in the specific context of Algeria.

The originality of our work lies in its contribution to filling a research gap by providing concrete results and analyses on the influence of liquidity management strategies and forecasting methods. Our study not only informs decision-makers but also researchers interested in financial forecasting, AI applications and liquidity management in emerging economies. In this way, our research opens new perspectives and provides a framework for future studies in this field in Algeria.

To address the main research question, the related sub-questions, and to test the hypotheses, two complementary approaches will be employed: a descriptive approach and an analytical approach. The descriptive approach involves comprehensive documentary research, drawing on academic publications, books, reports, and relevant websites to establish a clear understanding of the conceptual and institutional framework surrounding central bank liquidity and its key determinants. This foundation clarifies how liquidity is defined, the roles of its main components, and the critical importance of accurate liquidity forecasting for effective monetary policy.

The first chapter introduces the fundamental concepts of liquidity and its importance in financial management. It first examines the factors influencing liquidity and the connection between liquidity types before concluding with an analysis of how liquidity has evolved over time in Algeria. The second chapter focuses on liquidity management strategies and forecasting methods, reviewing prior research on forecasting and the challenges involved, as well as the implications for financial performance. The third chapter presents an empirical comparison of traditional and AI-based forecasting methods using data from 2015 to 2023. This chapter evaluates the performance of these models in predicting central bank liquidity, with the aim of identifying the most effective approaches to improve liquidity management.

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Chapter I: Liquidity in the Banking System

Introduction of the First Chapter

Since the 2008 financial crisis, bank liquidity has attracted increasing attention in economic literature. It is now recognized as a key factor in ensuring the stability and proper functioning of financial systems. Disruptions in liquidity can have significant impacts not only on banks but also on the broader economy, often leading to systemic risks.

This chapter aims to examine the main aspects of bank liquidity, including its components, the factors influencing it and the economic risks it entails. A thorough understanding of these elements is crucial for assessing financial stability.

To achieve this objective, the chapter is structured as follows:

- **Section 1:** Concept of Banking Liquidity.
- **Section 2:** The Relationship between different Types of liquidity.
- **Section 3:** The determinants of central bank liquidity in Algeria.

Section 1: Concept of Banking Liquidity

Liquidity, a key concept in economics, refers to the ability to meet financial obligations by converting assets into cash. It is viewed as a dynamic flow essential to the functioning of central banks, commercial banks, and financial markets. However, factors like market imperfections can disrupt this flow, leading to illiquidity. This section introduces the concept and associated risks of liquidity.

1. Definition of bank liquidity

Liquidity is fundamentally linked to money, as it serves as the liquid asset in the economy, facilitating transactions without the need for conversion. The introduction of money as a medium of exchange has enhanced economic efficiency by resolving the "double coincidence of needs" problem and reducing transaction costs (Mishkin, 2013, p53). Unlike other assets, which must be converted into money to be exchanged, money itself is readily accepted, underscoring its central role in maintaining liquidity within the banking system. Banks act as liquidity providers and financial intermediaries, mobilizing funds from surplus units (lenders) to finance deficit units (borrowers), ensuring the continuous flow of capital within the economy.

Bank liquidity refers specifically to a financial institution's ability to meet short-term obligations while maintaining stability and solvency, even in times of stress. This includes cash or assets that can be quickly converted into cash with minimal loss in value (Nikolaou, 2009). According to Monique Beziade, liquidity encompasses holdings such as central bank money, cash on hand and interbank credit accounts, which can be accessed to meet immediate needs. Mandatory reserves are a key indicator of a bank's financial health, as they reflect the bank's ability to fulfill obligations on time, ensuring smooth operation under both normal and stressed market conditions.

Beyond the availability of cash, liquidity also involves the efficient management of assets to meet both expected and unexpected obligations. This includes the use of highly liquid assets, such as short-term government securities, which can be sold with minimal loss. Liquidity is also shaped by the timing and structure of a bank's assets and liabilities, with less liquid assets maturing later to provide funds when needed.

2. Types of bank liquidity

Some studies classify liquidity within a financial system into three main categories: central bank liquidity, market liquidity, and funding liquidity (Nikolaou, 2009). However, other researchers advocate for a two-dimensional view of financial (market) liquidity, focusing solely on funding liquidity and market liquidity. This perspective is grounded in the belief that the central bank's role as a liquidity provider during financial crises merely mitigates the effects of such crises without resolving their underlying causes. Moreover, it is argued that the central bank often struggles to distinguish with certainty between illiquid and insolvent banks (Sekoni, 2015, p. 5).

2.1. Central bank liquidity

Central bank liquidity refers to the central bank's ability to provide the necessary liquidity to the financial system. It is typically measured by the amount of liquidity injected into the economy, specifically the flow of the monetary base[1] from the central bank to financial institutions. This is closely related to central bank operations liquidity, which refers to the amount of liquidity provided through the central bank auctions to the money market according to the «monetary policy stance» (Nikolaou, 2009, p. 11).

The monetary policy stance is determined by the central bank's operational target, typically the key policy rate, which serves as its primary control variable. To maintain this stance, the central bank uses various instruments, to regulate liquidity in the money market. These liquidity adjustments are directly reflected in the central bank's balance sheet, ensuring that interbank rates remain closely aligned with the target policy rate.

2.2. Funding liquidity

According to The Basel Committee of Banking Supervision, funding liquidity is «the ability of banks to meet their liabilities, unwind or settle their positions as they come due» (Basel Committee on Banking Supervision, 2008, p. 1).

Funding Liquidity is defined as a bank's ability to meet financial obligations on time. It reflects the institution's capacity to obtain external financing when necessary to manage withdrawal risks. Funding Liquidity ensures that a bank can mobilize resources to cover short-term and medium-term commitments while maintaining financial stability.

Drehamann and Nikolaou (2009) argued that a bank is considered to have enough funding liquidity (i.e. liquid) as long as its cash outflows are less to or of equal proportion with the cash inflows and the stock of money held by the bank. Their argument is based on the understanding that funding liquidity is a flow concept which they mathematically represented as follows;

$$\textbf{Outflows} \leq \textbf{Inflows} + \textbf{Stock of money}$$

Nikolaou (2009) stressed the importance of bank's funding liquidity as the means of distributing liquidity in the financial system. Therefore, he maintained that banks must ensure adequate liquidity at all times.

2.3. Market liquidity

Market liquidity refers to the ability to buy or sell assets quickly, at low cost and with minimal price impact. A highly liquid market ensures that transactions can occur smoothly, maintaining market efficiency and financial stability (Nikolaou,2009).

Market liquidity is characterized by four key dimensions:

- **Immediacy:** The speed at which transactions can be executed.
- **Breadth**: The cost of obtaining liquidity, often measured by the bid-ask spread.

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[1] The monetary base or M0, represents the total money supply in the economy. It consists of currency (banknotes) in circulation and bank's reserves held at the central bank.

- **Depth:** The ability to execute large transactions without significantly affecting prices.
- **Resilience**: The speed at which prices return to normal after market disruptions.

There are two primary types of market liquidity:

- **Interbank market liquidity**: This ensures financial system stability by allowing banks to lend and borrow short-term funds from one another, facilitating daily operations.
- **Asset market liquidity:** This enables investors to buy or sell securities without significant price fluctuations. Highly liquid assets can be traded quickly without major losses, whereas illiquid assets may experience substantial price changes.

While market liquidity facilitates the efficient transfer of funds between economic agents, it does not increase the overall money supply. Only central banks can inject additional liquidity into the financial system by adjusting monetary policy tools.

3. Determinants of central bank liquidity

To understand the factors influencing banking system liquidity, it is essential to first examine the central bank's balance sheet.

3.1. Central bank balance sheet

Determinants of liquidity are items on the central bank's balance sheet that influence banking system liquidity. Fluctuations in these determinants can either absorb or release liquidity into the banking system, affecting the central bank's ability to manage liquidity effectively. Understanding the central bank's balance sheet is therefore crucial for analyzing liquidity conditions.

Table 1.1 : The central bank's balance sheet

Assets	Liabilities
Net Foreign assets (NFA)	Currency in circulation (CIC)
Net Government Position (NGP)	Banks reserves (BR)
Central bank operations (CB)	Other items

Source : Central Bank of West African States

In this stylised balance sheet, the elements on the liabilities side of the balance sheet represent central bank money and as such can only be liabilities. The elements on the asset side of the balance sheet are netted in the above representation but can be both assets and liabilities when they appear on a detailed central bank balance sheet. Each of the components plays a significant role in the operation of both the central bank and the wider economy, if only because their variation will naturally impact on the availability of reserves to the banking system. Therefore, understanding the nature and changes in the components of the central bank's balance sheet is important for understanding the economy as a whole (Blake, 2015, p. 8).

4. The factors of central bank liquidity

Faced with outflows, economic agents may request the conversion of their deposits into currency, prompting banks to use their reserves. If reserves are insufficient, banks turn to interbank markets or the central bank for liquidity. These needs reflect the demand for central bank money, which is essential to the smooth operation of the monetary system. As a result, the factors that influence bank's liquidity and thus their need for refinancing, are considered the determinants of central bank liquidity. These determinants are primarily found in the central bank's balance sheet (Brana & Cazals, 2014, p.72).

4.1. Autonomous factors of banking liquidity

Autonomous factors of banking liquidity are balance sheet items, such as currency in circulation or government deposits, that affect liquidity independently of monetary policy. Their fluctuations influence bank's reserve levels and refinancing needs.

4.1.1. Net Foreign Assets (NFA)

Transactions between a resident and a non-resident involve exchanging domestic currency for foreign currency or vice versa. These exchanges go through banks, which need to acquire foreign currencies on the foreign exchange market when transactions are in deficit or sell them when they are in surplus. Specifically (Delaplace, 2013, p. 103):

- **Surplus of resident-non-resident exchanges**: When the exchanges are in surplus, residents hold claims in the form of foreign currencies, which they transfer to their banks. The banks then sell these foreign currencies on the foreign exchange market. If the central bank buys these currencies, it exchanges them for central bank money, which increases banking liquidity.
- **Deficit of resident-non-resident exchanges**: On the other hand, if the exchanges are in deficit, residents owe debts to non-residents, which they must settle in foreign currencies. They obtain these currencies from their banks, which, in turn, acquire them on the foreign exchange market in exchange for central bank money, thus decreasing banking liquidity.

Movements in foreign currencies with foreign entities directly influence banking liquidity. When the central bank's sales of currencies to banks are lower than its purchases of currencies from commercial banks, the central bank acquires a net amount of foreign currencies, improving banking liquidity and reducing refinancing needs. Conversely, when the central bank's sales of currencies to banks exceed its acquisitions, this results in a net sale of foreign currencies, decreasing banking liquidity and increasing refinancing needs.

4.1.2. Net Government Position (NGP)

The Treasury holds an account with the Central Bank to collect its revenues and make payments, thus influencing banking liquidity. When the Treasury makes public spending, such as paying salaries or repaying loans, the balance of its account decreases, which increases banking liquidity. Conversely, tax receipts or the collection of Treasury bonds increase the account balance, reducing banking liquidity. Transactions between the Treasury, central administrations, and financial agents pass through current accounts at the Central Bank, creating movements of central bank money. For example, if the payments from banks to the Treasury exceed those made by the Treasury, the Treasury's deposits increase, which reduces banking liquidity. This dynamic varies throughout the year, such as at the end of the year in certain countries, where local tax payments and income tax settlements lead to a temporary decrease in liquidity. Finally, by managing sight deposits, the Treasury causes leaks of money generated by banks, in proportion to its market share in these deposits, which also affects banking liquidity (International Monetary Fund, 2010).

4.1.3. Currency In Circulation (CIC)

Currency in circulation plays a key role in influencing banking liquidity. It refers to the amount of cash in circulation, which fluctuates based on the withdrawals and deposits made by economic agents (households and businesses). These fluctuations typically follow a seasonal and monthly pattern. For example, at the end of the month and the beginning of the following month, there is an increased demand for liquidity due to salary payments, resulting in a rise in fiduciary circulation. Conversely, in the middle of the month, agents tend to reintroduce their liquidities into banks through deposits or savings, reducing the amount of cash in circulation.

In a developed financial system, the issuance of cash is regulated by central banks and stays balanced with demand. Commercial banks manage this demand according to the preferences of agents for liquidity, which are influenced by psychological and socio-economic factors. While these seasonal variations are predictable in the short term, they become less precise over the medium and long term due to external factors like holidays, during which fiduciary circulation increases.

However, in the event of an economic crisis, where depositors rush to withdraw their funds out of fear of insolvency, excessive demand for cash can destabilize banking liquidity. This leads to a reduction in available liquidity within the banking system, which could even cause the failure of one or more institutions. This phenomenon highlights the importance of managing fiduciary circulation to maintain banking stability (European Central Bank, 2002).

5. Risks associated with liquidity

According to Sardi (2002, p. 43) highlights that «liquidity risk, or more precisely the risk of illiquidity, refers to a bank's inability to meet its obligations due to the impossibility of obtaining the necessary funds».

The definition adopted by the Algerian regulatory authorities, according to Regulation No. 11-08 of November 28, 2011, of the Bank of Algeria on the internal control of banks and financial institutions (Article 2), specifies that liquidity risk is the risk of failing to fulfill obligations or to liquidate or adjust a position, due to market conditions, within a given timeframe and at an acceptable cost.

In this context, liquidity risk represents a critical challenge for banks, as it encompasses both the uncertainty of financial markets and the institution’s ability to meet its obligations.

Liquidity risk encompasses various forms, each with distinct characteristics and implications for financial institutions. We find that the primary types include:

5.1. Central bank liquidity risk

Central bank liquidity risk is generally considered non-existent in the literature, as central banks hold a monopoly on issuing base money and can always supply liquidity as needed to maintain equilibrium in the banking system. Unlike financial institutions, central banks cannot face traditional liquidity problems unless there is no demand for domestic currency, which could occur in extreme scenarios such as hyperinflation or a severe exchange rate crisis (Nikolaou, 2009).

While central banks may incur costs associated with liquidity provision, such as counterparty risk related to collateral valuation, monetary policy risks, or financial stability concerns, these do not constitute liquidity risk per se, as they do not compromise the central bank's ability to provide liquidity (Nikolaou, 2009).

5.2. Funding liquidity risk

The concept of funding liquidity risk has been acknowledged since Bagehot (1873) and refers to the probability that a financial institution may be unable to meet its obligations as they mature within a specific time horizon (Drehmann & Nikolaou, 2009). This risk arises when a financial intermediary lacks sufficient liquidity to settle its liabilities as they fall due (IMF, 2008). Its severity depends on the availability of liquidity sources and the institution's capacity to maintain financial stability over time (Matz & Neu, 2006). Funding liquidity risk is influenced by the accessibility of liquidity sources and the ability to adhere to budget constraints over a given period. Unlike funding liquidity, which is a binary state, funding liquidity risk fluctuates and is influenced by financial conditions (Drehmann & Nikolaou, 2009). While generally stable, it may occasionally surge, often triggered by disruptions in market liquidity or broader financial risks (Brunnermeier & Pedersen, 2007).

Drehmann and Nikolaou (2009) find that funding liquidity risk shares similarities with market liquidity risk, being generally low and stable but prone to occasional spikes (e.g., heightened during periods of financial turmoil). This observation aligns with Matz and Neu (2006), who consider liquidity risk a consequential risk that escalates following spikes in other financial risks, such as market liquidity risk.

5.3. Market liquidity risk

Market liquidity risk refers to the inability to trade assets at a fair price with immediacy. It represents the systematic, non-diversifiable component of liquidity risk, which has two key implications. First, liquidity risk is common across different markets, a phenomenon supported both theoretically and empirically across stocks, bonds, and equity markets. Liquidity risk can also propagate across interbank and asset markets, amplifying its overall impact (Brunnemeier and Pedersen, 2007).

The second implication is that systemic liquidity risk should be priced into assets. In asset pricing models, market liquidity risk is often treated as a cost or premium that influences asset prices positively (Chordia et al., 2005). This premium affects market decisions, such as optimal portfolio allocation, and market practices, including transaction costs. The larger the premium, the greater the market liquidity risk. Typically, asset pricing models measure liquidity risk as the covariance (commonality) between liquidity measures and market returns. Liquidity risk moves with contemporaneous returns and can also predict future returns based on current liquidity risk estimates. Thus, asset prices reflect liquidity costs tied to liquidity risk.

The behavior of market liquidity risk has been well-documented. Normally, liquidity risk is low and stable, with high liquidity risk being rare. This episodic nature often arises from downward liquidity spirals driven by mutually reinforcing funding and market illiquidity. However, such events are uncommon due to the benefits of cooperation in trading (Brunnemeier and Pedersen, 2007).

Finally, market liquidity risk has profound implications for financial stability. While individual liquidity risk, such as isolated bank failures, may have limited consequences and could even help restore financial health in certain situations (Allen and Gale, 1998), systemic liquidity risk can trigger financial crises that damage financial stability, disrupt resource allocation, and affect the real economy. Given its importance to financial stability, systemic liquidity risk is a key concern for policymakers. However, due to the complex linkages between different types of liquidity risks, a holistic view of liquidity flows across the system is necessary to fully understand and address market liquidity risk.

Section 2: The relationship between different types of liquidity

To understand the relation between different types of liquidity, it is important to analyze liquidity shortages, which are conceptually distinct from liquidity risks. While the two phenomena are closely related, they differ in subtle yet significant ways. Liquidity shortages refer to an actual insufficiency of liquid assets or funding sources to meet immediate obligations, whereas liquidity risks pertain to the potential for such shortages to arise due to internal or external factors. This distinction is critical for developing a nuanced understanding of liquidity dynamics within financial systems.

1. Liquidity shortages

Liquidity Shortages refers to a situation in which a financial institution is unable to obtain cash or other means of payment at a reasonable cost. This inability to access short-term funding—despite having assets—can prevent the institution from meeting its immediate obligations, potentially triggering failures that may have broader destabilizing effects on the financial system.

There are generally three main types of liquidity shortages:

1.1. Shortage of central bank liquidity

A shortage of central bank liquidity is one of the less severe forms of liquidity constraints and arises when financial institutions lack the reserve balances they aim to maintain. This situation can result from either an insufficient aggregate supply of reserves or inefficiencies in their distribution within the financial system. When such shortages occur, institutions may struggle to meet their immediate payment obligations, potentially leading to a disruption in the payments system. This is often reflected in a sharp increase in overnight interest rates, with possible spillover effects on other segments of the money market. Importantly, these liquidity shortages typically occur without concerns regarding the solvency of specific institutions.

When liquidity shortages stem from distributional inefficiencies, they are usually caused by technical issues, such as operational failures or poor liquidity management. Notable examples include the Bank of New York's computer malfunction on November 20, 1985, which led to a significant cash shortage despite the institution's financial soundness, and the disruptions in September 2001. In such cases, the primary challenge for central banks is the misallocation of reserves, where some institutions hold excess liquidity while others face acute shortages due to systemic breakdowns in payment mechanisms.

Additionally, a shortage of central bank liquidity can result from an overall inadequate supply of reserves in the system. This may be due to errors in central bank forecasting of factors affecting liquidity conditions, such as unexpected fluctuations in government balances or a sudden, unforeseen surge in demand for reserves. For instance, in early August 2007, heightened uncertainty regarding future funding availability led to a sharp increase in the demand for reserves, exerting upward pressure on overnight rates. Initially, many central banks struggled to maintain their policy targets, prompting an immediate policy response to inject additional reserves into the system in an attempt to alleviate the liquidity shortfall (Cecchetti & Disyatat, 2009).

1.2. Acute funding liquidity shortages at specific institutions

The second type of liquidity shortage arises when a particular institution faces a severe funding liquidity crisis, often driven by concerns over its solvency. In such cases, counterparties may become unwilling to engage in transactions with the institution, exacerbating its liquidity constraints. This situation typically results from a flawed business strategy-whose weaknesses often become apparent only in hindsight-that has left the institution vulnerable to sustained cash outflows. Given the significant perception of insolvency, the liquidity shortage tends to persist, necessitating bridge financing to provide the institution with time for fundamental restructuring.

The primary risk associated with acute institution-specific liquidity shortages, and the main justification for any official intervention, is the potential for contagion and systemic spillover effects that could threaten the stability of the broader financial system. In such scenarios, the critical factor in determining whether liquidity support should be provided is the institution's systemic importance. The distinction between illiquidity and insolvency becomes secondary in these considerations. Notable examples of acute funding liquidity shortages requiring lender-of-last-resort **(LOLR)** support include the rescue of Continental Illinois in 1984 and the liquidity assistance extended to various banking and non-banking financial institutions during the global financial crisis (Cecchetti & Disyatat, 2009).

1.3. Systemic shortage of funding and market liquidity

The most severe form of liquidity shortage occurs when both funding and market liquidity experience a widespread collapse, leading to systemic disruptions. This type of crisis is driven by a loss of confidence and coordination failures among market participants, ultimately causing key financial markets to break down. Just as financial institutions can experience liquidity runs, markets themselves can face similar dynamics.

A striking example of this phenomenon was observed in the immediate aftermath of the Lehman Brothers bankruptcy in September 2008, where market and funding liquidity evaporated simultaneously, leading to severe instability in both the financial system and the broader economy.

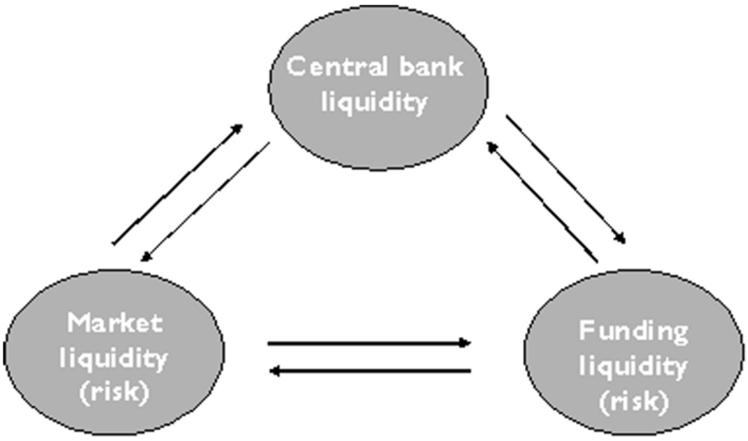
Such crises typically arise from heightened uncertainty regarding asset values and the financial health of counterparties. When market participants withdraw due to uncertainty, liquidity dries up, making it difficult to convert assets into cash. This, in turn, creates funding liquidity constraints for financial institutions, further increasing counterparty credit risk. The resulting feedback loop—where deteriorating market liquidity exacerbates funding shortages and vice versa—amplifies the crisis.

Historical examples include the 1987 stock market crash, where a sudden liquidity freeze led to widespread financial turmoil. Similar liquidity-driven disruptions have also played a critical role in more recent financial crises (Cecchetti & Disyatat, 2009.).

2. From liquidity risk to shortage: Understanding liquidity linkages

We argue that the three distinct types of liquidity: central bank liquidity, market liquidity, and funding liquidity are intricately interconnected. To explore this, we analyze their interrelationships through two scenarios: normal periods and turbulent periods. In normal periods, defined by low liquidity risk, a positive feedback loop forms between these liquidity types, enhancing stability within the financial system. However, during turbulent periods marked by high liquidity risk, the same linkages may turn problematic, potentially triggering a negative feedback loop that destabilizes the financial system.

Figure 1.1 : The three liquidity nodes of the financial system



Source: Nikolaou (2009)

2.1. Interconnections of liquidity in normal periods

In normal circumstances, liquidity flows smoothly between the three types central bank liquidity, market liquidity, and funding liquidity, forming a self-sustaining cycle that promotes the stability of the financial system. The central bank, tasked with ensuring overall liquidity provision, injects the necessary liquidity into the financial system to offset any shortfalls. This liquidity is then allocated to banks, which redistribute it through various markets, such as interbank and asset markets, ensuring that liquidity-constrained entities can access the necessary funds.

Following this redistribution, the central bank assesses the new liquidity demands and adjusts its supply accordingly, perpetuating the liquidity cycle (ECB, 2004). Each liquidity type serves a distinct role: the central bank provides neutral liquidity, financial markets facilitate circulation and redistribution, and funding liquidity ensures the efficient allocation of resources among economic agents. Given their interdependence, the proper functioning of each liquidity type is crucial to maintaining a liquid financial system.

For this process to remain effective, liquidity supplied by the central bank must circulate freely, with market liquidity ensuring its continuous redistribution and funding liquidity directing it efficiently within the system. Financial markets should remain liquid as long as there is sufficient aggregate liquidity, and each participant can access funding according to their needs. The availability of funding liquidity sources also determines financial institutions' ability to meet their obligations. In such a scenario, banks remain liquid as long as they can access sufficient liquidity from the markets or the central bank.

These dynamic fosters a stable financial environment, where liquidity flows seamlessly, enabling banks to access multiple funding sources based on cost efficiency (Drehmann & Nikolaou, 2009). By ensuring the efficient circulation of liquidity through markets and funding channels, this system helps mitigate financial vulnerabilities and supports overall financial stability.

2.2. Liquidity interconnections in unstable periods

Financial markets are often characterized by inefficiencies and asymmetric information, which can lead to coordination failures among key stakeholders, including banks, depositors, and market participants. During stable periods, liquidity follows a virtuous cycle, supporting financial stability. However, in times of turbulece, this cycle can reverse, giving way to a vicious circle of heightened liquidity risk. This process triggers a liquidity spiral that threatens the stability of the entire financial system.

Nikolaou (2009) highlights that liquidity risk is endogenous to the financial system. In other words, the liquidity-driven stability observed in normal conditions can transform into instability during crises. The author also explores the interplay between the three forms of liquidity and how they are affected by liquidity risk. Although these forms remain interconnected during turbulent times, they instead act as channels for liquidity risk propagation, further destabilizing the financial system.

Nikolaou (2009) illustrates a scenario in which a bank is confronted with considerable funding liquidity risk. The study highlights how this risk can propagate to the wider financial market through market liquidity risk, while also analyzing the pivotal role that central bank liquidity plays in alleviating such crises.

2.2.1. Propagation of liquidity risk

Can propagate through funding liquidity risk and market liquidity risk:

2.2.1.1. Through funding liquidity risk

Funding liquidity risk is central to banking activity. Through their intermediation role, banks transform liquid resources into illiquid assets (Diamond & Dybvig, 1983). In other words, their primary function within the financial system is to provide liquidity by channeling deposits into long-term investments. Banks collect liquidity from depositors and allocate it to investors in the form of illiquid assets (such as loans). This maturity transformation allows banks to finance investments by converting short-term liabilities into long-term assets. However, this very process also introduces fragility into the banking system (Diamond & Rajan, 2001).

When maturity transformation is disrupted, bank's role as liquidity providers becomes a source of instability. This inherent fragility exposes banks to funding liquidity risk. Given the structural weaknesses of their business model, combined with market inefficiencies and asymmetric information between depositors and banks, liquidity shortages can arise. In extreme cases, these conditions may lead to bank runs, considered the most severe manifestation of funding liquidity risk. According to Diamond & Dybvig (1983), bank runs occur when depositors, fearing insolvency, rush to withdraw their funds, prompting a liquidity crisis that the bank cannot withstand. Even solvent institutions may collapse under such pressure.

2.2.1.2. Through market liquidity risk

By interbank market and asset market:

- **By Interbank market:**

Funding liquidity risk at an individual bank level does not, in itself, pose a direct concern for regulatory authorities. However, the situation becomes critical when this risk escalates into a systemic threat, spreading to other banks. Given the strong interconnections within the interbank market, the failure of a single bank due to excessive exposure to funding liquidity risk can disrupt the entire system. A weakened interbank market can, in turn, trigger a broader liquidity shortage, increasing the risk of multiple bank failures.

This chain reaction stems from the close ties between banks in the interbank market, where funding liquidity risk is intrinsically linked to market liquidity risk. A bank run triggered by depositor's concerns can rapidly extend to other institutions, leading to a widespread banking panic. Additionally, asymmetric information among banks erodes trust, discouraging interbank lending due to concerns over counterparty insolvency. As a result, the interbank market may seize up, causing a liquidity freeze that heightens the risk of widespread banking failures, unless the central bank intervenes (Oubdi & Alaoui Mdaghri, 2019).

- **By Asset market:**

Asset markets serve as an additional channel for the transmission of both funding liquidity risk and market liquidity risk. When banks struggle to secure refinancing through the interbank market due to liquidity shortages, they are compelled to turn to asset markets, liquidating assets at discounted prices to obtain cash. This forces banks to restructure their portfolios, prioritizing highly liquid assets while offloading fewer liquid ones.

In an environment where financial markets are incomplete, large-scale asset liquidation exerts downward pressure on prices, as markets have a limited capacity to absorb such sales. This, in turn, heightens asset price volatility and discourages market participation due to increased uncertainty. Consequently, asset prices decline below their intrinsic values, further exacerbating liquidity shortages across the asset market (Oubdi & Alaoui Mdaghri, 2019).

3. The dynamic relationship between market liquidity and funding liquidity

The relationship between funding liquidity risk and market liquidity risk is not unidirectional; rather, they reinforce each other, creating a potential cycle of market illiquidity. This phenomenon can occur even in a regulated financial system where assets are marked to market. When asset prices decline, banks must reflect these losses on their balance sheets, prompting them to liquidate additional assets, often at distressed prices, to meet regulatory solvency requirements. This process exacerbates liquidity pressure, further driving down asset prices and heightening the risk of interbank liquidity contagion.

Moreover, securitization plays a role in shaping the connection between the market and funding liquidity risk. While it serves as a financing tool and a mechanism for transferring credit risk off balance sheets, securitization has also diminished the traditional role of banks in liquidity transformation. Modern banks create assets through securitization, acting as market participants that price and evaluate them, thereby increasing their reliance on external institutions such as rating agencies. Consequently, banks have become more dependent on market-based financing, making their lending capacity highly sensitive to financial market conditions. As a result, the link between funding and market liquidity has strengthened, facilitating faster and more direct transmission of risks.

Brunnermeier and Pedersen (2009) developed a model that highlights the relationship between funding liquidity and market liquidity. According to their findings, market liquidity, provided by traders, depends on their ability to secure financing, including capital and margin requirements. Conversely, trader's access to funding is influenced by market liquidity. This interdependence becomes especially pronounced during financial crises, strengthening the link between the two and potentially leading to liquidity spirals (Oubdi & Alaoui Mdaghri, 2019).

Section 3: The determinants of central bank liquidity in Algeria

This section presents the main factors influencing banking liquidity in Algeria, highlighting their evolution and impact on the financial system.

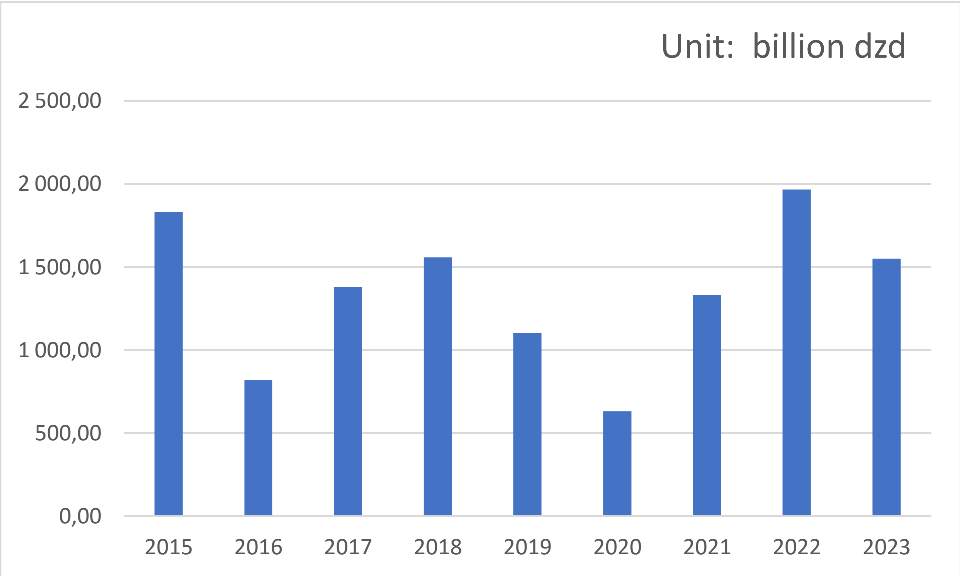
1. Banking liquidity in Algeria

Bank liquidity remains a key indicator of the financial health of a banking system. In Algeria, the period from 2015 to 2023 was marked by significant fluctuations in bank liquidity, driven by various autonomous factors. Understanding these factors is crucial for analyzing liquidity mechanisms and enables the Bank of Algeria to anticipate and manage liquidity effectively, ensuring financial stability.

1.1. Banking liquidity situation from 2015 to 2023

The graph shows a fluctuating pattern over the years. There's a noticeable peak in 2022, followed by a decline in 2023. The lowest point appears to be in 2020, while 2015 and 2018 also exhibit relatively high values.

Figure 1.2 : Annual Evolution of Bank Liquidity



Source: Elaborated by us via Microsoft Excel

To better analyze its evolution, we will divide the eight-year period into five distinct phases. Our objective is to identify the key factors influencing liquidity fluctuations in each phase to gain a deeper understanding of liquidity management.

The graph illustrating the liquidity trends can be divided into key periods:

- **2015 to 2016:** Sharp decrease in bank liquidity.
- **2017 to 2018:** Recovery and increase in bank liquidity.
- **2019 to 2020:** Decrease in bank liquidity.
- **2021 to 2022:** Progression of bank liquidity.

- **The year 2023**: Decrease in liquidity.

2. Analysis and trends of bank liquidity in Algeria

As mentioned earlier, bank liquidity is influenced by several key factors, including Net Foreign Assets (NFA), Currency in Circulation (CIC) and the Net Government Position (NGP).

It is important to note that an increase in NFA contributes to increasing bank liquidity, whereas Treasury operations and currency in circulation have a restrictive effect, as illustrated in the graph above.

- **2015 to 2016: Sharp decrease in bank liquidity**

According to the 2015 and 2016 Annual Reports of the Bank of Algeria, the decline in banking liquidity during this period was mainly due to two factors. First, the drop in oil prices led to a decrease in oil revenues. In 2015, this decline resulted in a 41% reduction in deposits from the hydrocarbons sector, directly impacting banking resources. Second, the increase in credit to the economy also contributed to this situation. Banks intensified their lending to productive sectors, with a 16.57% growth in bank credit in 2015, which increased the demand for liquidity and reduced available reserves. These combined factors explain the deterioration of banking liquidity in Algeria during this period.

Net Foreign Assets: In 2015, net foreign assets declined by 2.3%, amounting to a decrease of 359.1 billion dinars. This reduction was mainly due to the conversion effect of foreign exchange reserves into dinars. However, the most significant impact on banking liquidity came from the overall balance of payments deficit, which led to a contraction of 2,741.7 billion dinars in banking liquidity. In 2016, this trend intensified, with a more pronounced 18.1% decline in NFA, dropping from 15,375.4 billion dinars in 2015 to 12,596 billion dinars. This further reduction contributed to an additional liquidity contraction, to a decrease of 26.03 billion dollars in dinar equivalent.

Net Government Position: In 2015, public treasury deposits at the Bank of Algeria decreased by 2,336.6 billion dinars, mainly due to withdrawals from the Revenue Regulation Fund (RRF). The government mobilized 2,277.4 billion dinars from the RRF, reducing its balance from 4,335.6 billion dinars at the end of 2014 to 2,058.2 billion dinars at the end of 2015. This mobilization injected liquidity into the banking system, partially offsetting the negative impact of the NFA decline. In 2016, liquidity injections continued, reaching 1,318.2 billion dinars, as the government withdrew additional funds from the RRF to finance the Treasury deficit.

Currency in circulation: Cash circulation also played a key role in banking liquidity trends. In 2015, currency circulation outside the Bank of Algeria increased by 449.2 billion dinars, marking a 12.3% rise compared to the previous year (15% in 2014). This expansion acted as a liquidity-draining factor in the banking system, further tightening liquidity conditions. In 2016, although the increase was slightly lower at 389.1 billion dinars, it continued to reduce banking liquidity as deposits were converted into cash.

- **2017 to 2018: Recovery and increase in bank liquidity**

In 2017, banking liquidity continued to decline due to persistent balance-of-payments deficits. During the first ten months of the year, liquidity dropped from 820.9 billion dinars at the end of 2016 to 482.4 billion dinars by October 2017, despite the Bank of Algeria's resumption of refinancing operations.

However, with the implementation of unconventional financing in November 2017, liquidity rebounded significantly, reaching 1,380.6 billion dinars by the end of December 2017. This trend continued into 2018, with liquidity further increasing to 1,557.6 billion dinars by December 2018.

Net foreign assets: In a context of moderate depreciation of the Algerian dinar against the US dollar, net foreign assets (NFA), representing foreign exchange reserves expressed in dinars, declined by 15.5%, decreasing from 11,227.4 billion dinars at the end of 2017 to 9,485.6 billion dinars at the end of 2018. This decline was mainly due to the deficit in the overall balance of payments, leading to a reduction in banking liquidity equivalent to -15.82 billion US dollars in dinars.

Net Government Position: Net credit to the state saw a significant increase of 34.8%, reaching 6,325.7 billion dinars in 2018, compared to 4,691.9 billion dinars in 2017. This rise was primarily driven by an increase in credit from the Bank of Algeria to the state, which grew by 1,890.4 billion dinars, rising from 1,967.4 billion dinars at the end of 2017 to 3,857.8 billion dinars at the end of 2018. Conversely, commercial bank's credit to the state decreased to 1,362.5 billion dinars at the end of 2018, down from 1,688.7 billion dinars in 2017, a decline linked to the state treasury's net debt reduction towards commercial banks.

Currency in Circulation: Cash circulation increased by 209.9 billion dinars in 2018. This rise reflects a conversion of deposits into cash, constituting an autonomous factor in reducing banking liquidity.

- **2019 to 2020: Decrease in bank liquidity**

During the first nine months of 2020, banking liquidity experienced a significant contraction, plummeting from 1,100.9 billion dinars at the end of 2019 to 461.8 billion dinars by September 2020. This sharp decline of 639.1 billion dinars (-58.1%) was primarily driven by the current account deficit in the balance of payments and the economic impact of the COVID-19 pandemic.

However, liquidity management measures introduced by the Bank of Algeria in 2020 helped stabilize the situation. As a result, banking liquidity rebounded to 632.1 billion dinars by the end of 2020, reflecting a 36.9% increase compared to September 2020.

Net Foreign Assets: In 2020, the annual average exchange rate of the dinar depreciated by 6.3% against the dollar, contributing to a further decline in net foreign assets (NFA). These reserves, expressed in dinars, fell from 7,598.7 billion dinars at the end of 2019 to 6,518.32 billion dinars by the end of 2020.

Regarding banking liquidity, the overall balance of payments deficit resulted in a liquidity variation of -16.4 billion dollars in 2020, compared to -16.9 billion dollars in 2019.

Net Government Position: Net credit to the State recorded a 34.4% increase, rising from 7,019.9 billion dinars at the end of 2019 to 9,433.8 billion dinars by the end of 2020.

- Net credit from the Bank of Algeria increased significantly, reaching 6,480.3 billion dinars in 2020, an increase of 1,697.9 billion dinars compared to 924.5 billion dinars in 2019.
- Commercial bank's credit to the State also grew, rising from 1,051.1 billion dinars in 2019 to 1,320.8 billion dinars in 2020, reflecting an additional 269.7 billion dinars in lending.

Currency in circulation: In 2020, the circulation of banknotes and coins increased sharply by 703.1 billion dinars, surpassing the 510.8 billion dinars recorded in 2019. This acceleration in cash withdrawals highlighted a growing preference for liquid assets, acting as an autonomous factor in reducing banking liquidity.

- **2021 to 2022: Progression of bank liquidity**

As part of the special refinancing program implemented by the Bank of Algeria to introduce relief measures aimed at supporting economic activity in a challenging pandemic context, banking liquidity saw a 77% increase.

Following a sharp rise of 110.64% in 2021, banking liquidity continued to grow in 2022, albeit at a more moderate pace. It reached 1,966.41 billion dinars, up from 1,331.95 billion dinars in 2021, marking a 47.63% increase.

Net foreign assets: Net foreign assets grew by 0.63% in 2021, rising from 6,518.25 billion dinars to 6,559.01 billion dinars, mainly due to exchange rate effects following the euro's depreciation against the dollar. This growth accelerated significantly in 2022, with a 31.88% increase, reaching 8,650.40 billion dinars by year-end

Net Government Position: Net credit to the state surged by 37.95%, reaching 12,903.16 billion dinars by the end of 2021, up from 9,353.46 billion dinars the previous year. This increase was primarily driven by banking operations with the Treasury under the Special Refinancing Program.

Currency in circulation: In 2022, cash circulation grew by 10.14%, slightly surpassing the 9.35% recorded in 2021. This rise was primarily driven by elevated inflation, which surged from 7.23% to 9.27%, fueling higher demand for cash.

- **In 2023: decrease in liquidity**

Following significant growth in bank liquidity in 2021 and 2022, a 21.1% decline was recorded between 2022 and 2023, bringing the total to 1,551.45 billion dinars by year-end, compared to 1,966.41 billion dinars the previous year. This drop was primarily driven by lower exports, particularly hydrocarbons, the end of relief measures introduced during the health crisis, and monetary policy adjustments.

Net foreign assets: Despite lower hydrocarbon prices compared to the previous year, they remained favorable, enabling Algeria to accumulate more reserves. Consequently, net foreign assets increased by 9.0%, rising from 8,650.40 billion dinars at the end of 2022 to 9,427.28 billion dinars by the end of 2023.

Net Government Position: Net credit to the state recorded a modest increase of 2.0%, rising from 13,042.42 billion dinars at the end of 2022 to 13,298.17 billion dinars by the end of 2023. However, net credit provided by the Bank of Algeria declined significantly by 19.6%, while commercial bank's loans to the state saw a 12.0% increase, reaching 7,306.98 billion dinars in 2023, compared to 6,522.75 billion dinars in 2022.

Currency in circulation: Cash circulation contributed 46.7% to the growth of the money supply, this highlights a major challenge for financial inclusion in Algeria. To enhance inclusion through the adoption of modern payment methods, several initiatives were launched and were nearing completion by the end of 2023.

Conclusion of the First Chapter:

The objective of this chapter was to introduce the concept of liquidity and explore its significance within the context of Algeria. Various events and developments over time have highlighted the central role of liquidity in economic functioning. This chapter presented liquidity as a fundamental concept, emphasizing its relevance for financial stability and economic growth in Algeria.

Liquidity is commonly defined as the ability to meet financial obligations when they come due, without significantly affecting the asset's price. This concept is crucial for understanding both individual and institutional financial health.

Furthermore, the chapter explored the risks associated with liquidity, particularly in the context of Algerian economy. These risks, such as liquidity shortages and financial vulnerabilities, were analyzed to highlight the interconnectedness between liquidity and economic stability. Understanding these risks is essential for both policymakers and financial institutions in Algeria to navigate potential economic challenges.

Building on these insights, the next chapter will focus on *liquidity management by the central bank*. It will explore the strategies, tools, and frameworks used to ensure adequate liquidity, mitigate risks, and maintain financial stability in both normal and stressed conditions.

Chapter II: Liquidity management by the central bank

Introduction of the Second Chapter

The objective of this chapter is to present monetary policy as a fundamental tool for managing economic stability. As economies face various challenges, monetary policy plays a crucial role in stabilizing inflation, controlling interest rates, and promoting sustainable economic growth. Understanding the underlying principles and objectives of monetary policy is essential to grasp its significant influence on economic outcomes, particularly in the regulation of liquidity within the financial system. By analyzing how central banks implement monetary policy, we can better understand its impact on financial stability and the broader economy.

This chapter is structured as follows:

- **Section 1:** The concept and mechanisms of monetary policy.
- **Section 2:** Central bank and liquidity management.
- **Section 3:** Previous studies on monetary policy and liquidity management.

Section 1: The Concept and Mechanisms of Monetary Policy

This section provides an overview of monetary policy, focusing on its fundamental objectives and the mechanisms through which it affects economic activity. By examining the main goals pursued by central banks and the various channels of transmission, we aim to clarify how these tools are implemented in practice.

1. Monetary policy

Monetary policy refers to the actions and rules adopted by central banks to regulate the money supply and interest rates to achieve price stability.

As noted by Mazeri and Sadouni (2023) Monetary policy holds a central role in contemporary economic thought, serving as a key instrument through which governments intervene in and guide economic activity toward targeted objectives. It is employed to correct macroeconomic imbalances by managing the money supply, regulating liquidity within the banking sector, and influencing short-term interbank interest rates. These actions, facilitated by various monetary policy tools, aim primarily at maintaining price stability and fostering sustainable economic growth. Alongside fiscal policy, monetary policy represents one of the two principal levers available to public authorities to shape the pace and direction of economic activity in a market economy. It affects not only aggregate output and employment levels but also the general rate of inflation or deflation. Over recent decades, there has been a growing reliance on monetary policy, typically conducted by central banks, as the dominant mechanism for achieving macroeconomic stability, often taking precedence over fiscal interventions.

Monetary policy decisions are often influenced by domestic and external shocks that could threaten economic stability. In the short run, because prices and wages do not adjust immediately, changes in the money supply can influence output and employment. However, in the long run, monetary policy primarily affects inflation rather than real economic output.

2. Objectives of monetary policy

Every monetary policy, and more broadly, any type of policy, is designed to achieve specific objectives that are structured. These objectives can be categorized into three levels: final objectives, intermediate objectives and operational objectives.

2.1. The final objectives of monetary policy

Most economic studies emphasize that the ultimate goal of any economic policy is to enhance public welfare. However, this objective varies across countries due to differences in economic structures and systems. From a Keynesian perspective, government intervention is essential for stimulating economic growth and maintaining employment, highlighting the interconnected nature of macroeconomic objectives.

Building on this idea, Nicholas Kaldor introduced the "magic square" in 1971, a framework designed to balance four key policy goals. It is termed "magic" because achieving all four objectives simultaneously is highly challenging. Within this framework, monetary policy plays a crucial role not only in controlling inflation, as emphasized by monetarists, but also in fostering economic growth (Keynesian perspective), maintaining trade balance, and supporting employment.

The four key policy goals of the magic square are:

2.1.1. Economic growth

Achieving an acceptable rate of economic growth is a significant challenge for any economy. Enhancing economic growth inherently involves improving living standards, creating job opportunities, reducing unemployment, and strengthening overall economic performance through increased investment and production. To achieve a sustainable growth rate, it must exceed population growth while ensuring the optimal use of productive capacities and available resources. This allows for the absorption of the expanding labor force, a decline in unemployment and the adequate provision of goods and services, ultimately raising living standards.

2.1.2. Price stability

Managing inflation is essential, as failure to control it can distort economic indicators and undermine confidence in economic policy measures. To control inflation, monetary authorities employ various policy tools to regulate the money supply, ensuring it does not exceed the growth rate of real output. This process involves overseeing currency issuance through a strategic monetary framework that balances money supply with demand, fostering economic activity and expansion. The objective is to maintain a real national output growth rate that surpasses the increase in money supply. According to Kaldor, a zero percent inflation rate is ideal, as failing to contain inflation can significantly disrupt key economic indicators used for decision-making.

2.1.3. External balance

Ensuring external equilibrium in the balance of payments is essential for economic stability, as it reflects a country's financial position relative to other nations. A persistent deficit can signal excessive spending, leading to rising national debt and potential depreciation of the national currency. Maintaining a balanced balance of payments supports currency stability and smooth economic transactions, while abrupt currency fluctuations pose risks, particularly for economies with weaker currencies. To address imbalances, governments often intervene by regulating the money supply, adjusting interest rates, and influencing credit availability in commercial banks. Additionally, modifications in public and private spending may be necessary to restore stability. According to Kaldor, an optimal balance of payments should be zero or a positive percentage of GDP[2].

2.1.4. Low unemployment

This objective aims to achieve full employment of all productive resources while eliminating unemployment and negative social effects on society. In essence, it focuses on

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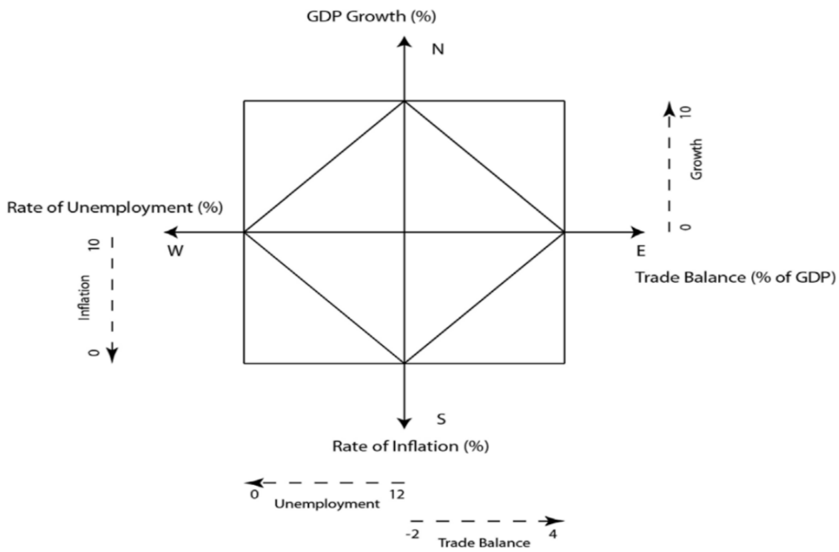
[2] an increase in real GDP is seen as an indicator of a healthy economy. Strong GDP growth often correlates with rising employment, as businesses expand production and hire more workers. This, in turn, boosts household incomes, leading to greater consumer spending and overall economic prosperity.

achieving full employment and minimizing the financial burden of unemployment benefits, which can hinder economic growth. However, full employment extends beyond just labor, it encompasses the optimal use of all production factors, including capital. According to Kaldor, increasing employment levels and reducing unemployment to its lowest possible rate ideally means achieving a 0% unemployment rate.

Figure 2.1:Graphical representation of the Kaldor's Magic Square



Source: (Rivano & Teixeira, 2016).

However, since the final objective cannot generally be achieved directly through monetary policy instruments, it is necessary to rely on intermediate targets that are more easily controllable and expected to have a direct influence on the desired outcomes.

2.2. The Intermediate objectives of monetary policy

Before introducing the intermediate objectives of monetary policy, it is essential to first understand the fundamental role that central banks play in ensuring monetary and financial stability.

2.2.1. Role of intermediate monetary targets

Monetary aggregates are useful targets for monetary policy when a stable relationship exists between them and nominal income, which combines real income growth and inflation. If this relationship holds, adjusting monetary aggregates can stabilize nominal income growth. However, this relationship is not always precise, making the effectiveness of monetary aggregates uncertain. Expansionary monetary policy may not always boost income and could lead to inflationary pressures in the long term (Latreche, 2012, p. 8).

2.2.2. Achieving monetary policy intermediate targets

To achieve the ultimate objectives of monetary policy, the Central Bank sets the following intermediate targets (Patat, 1993, p. 388):

- **Maintaining interest rate stability:** The Central Bank establishes an attractive interest rate to foster a favorable environment for investment and economic growth. According to Keynesian theory, a reduction in the interest rate should stimulate economic recovery. While Central Banks do not explicitly target this objective, they consider interest rate levels because they affect corporate investments and short-term capital flows.

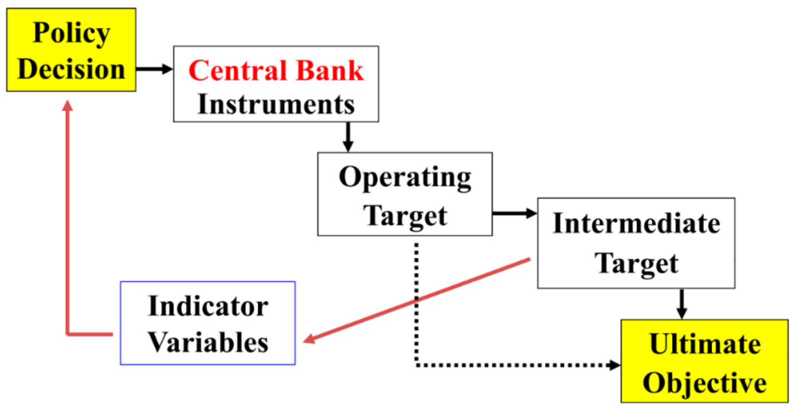
- **Ensuring exchange rate stability:** The Central Bank can use monetary policy instruments to influence the value of the national currency. Maintaining exchange rate stability at a level consistent with real economic activity has a positive impact on foreign trade.

- **Regulating the money supply at a balanced level:** Controlling the growth of the money supply is a central objective for monetarists. To prevent inflationary pressures, it is essential that the expansion of the money supply aligns with the growth rate of the real economy.

2.3. Operational objectives

The diversity of intermediate objectives necessitates the selection of operational objectives, which consist of monetary indicators and statistics that monetary authorities can effectively achieve in the short-term using the instruments at their disposal. For example, interbank market rates or the monetary base allocated to commercial banks enable these authorities to efficiently control the money supply.

Figure 2.2:The trajectory between policy decision and ultimate objective



Source: Mazeri, A., & Sadouni, M. (2023).

3. Criteria for choosing the policy instrument

Three criteria are considered when selecting a policy instrument: it must be observable and measurable, under the central bank's control, and capable of producing a predictable impact on the intended objective (Mishkin, 2013, p. 403).

3.1. Observability and measurability

A policy instrument must be easily observable and measurable to effectively signal the stance of monetary policy. While reserve aggregates like nonborrowed reserves are measurable, they suffer from reporting delays. In contrast, short-term interest rates, such as the federal funds rate, are instantly observable. However, nominal interest rates do not accurately reflect borrowing costs, as real interest rates depend on expected inflation, which is difficult to measure. Therefore, both instruments have limitations in terms of observability.

3.2. Controllability

For an instrument to be effective, the central bank must have strong control over it. While reserve aggregates are influenced by currency fluctuations, making them less controllable, short-term interest rates can be managed more precisely. However, since inflation expectations affect real interest rates, central banks cannot fully control them. This makes it unclear whether interest rates or monetary aggregates are the better policy tools.

3.3. Predictability of policy effects

A key requirement for a policy instrument is its ability to reliably influence economic goals like inflation and employment. Research suggests that

Interest rates have a stronger and more predictable link to inflation than monetary aggregates, leading many central banks to favor them as primary policy tools.

4. Monetary policy transmission impact on bank liquidity

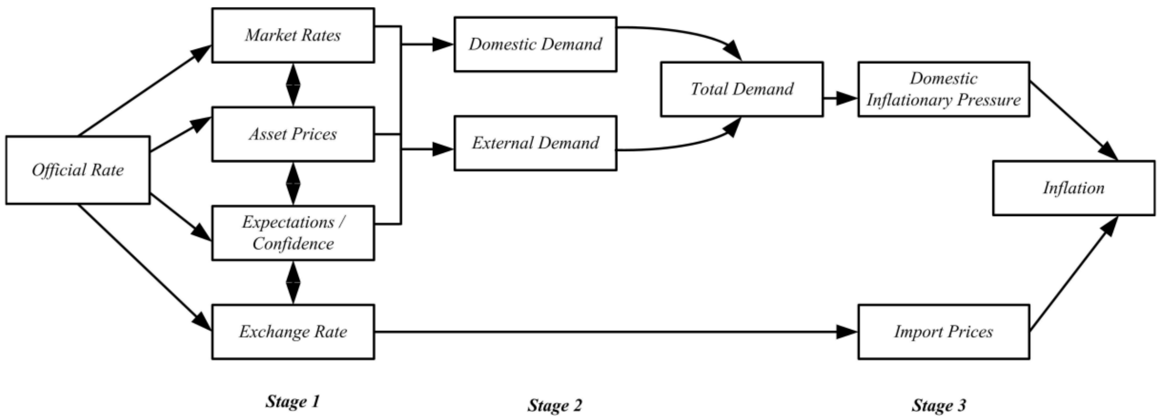
Monetary policy transmission channels are the mechanisms through which central banks implement their actions to achieve economic objectives. These channels influence the behavior of economic agents and liquidity levels by affecting the supply and demand of goods and services. Their effectiveness depends on factors like central bank credibility, policy goals, and the national economy's characteristics.

4.1. Interest rate channel

The interest rate channel is the main mechanism for monetary policy, involving a three-stage process (Murić, 2010, p. 4):

- **Stage 1:** Financial market adjustments, changes in policy rates affect other interest rates, influencing borrowing costs and asset prices, which, in turn, affect exchange rates and future expectations.
- **Stage 2:** Effects on aggregate demand, lower interest rates can encourage consumption by making borrowing cheaper, while higher rates promote saving and reduce consumption.
- **Stage 3:** Impact on GDP and inflation, increased demand can boost GDP, but excessive demand may cause inflation if the economy is near full capacity.

Figure 2.3:Interest Rates Channel



Source: Mehmed Murić, 2010

4.2. Credit channels

According to Mishkin (1996), the credit channel contains the following components:

4.2.1. The bank lending channel

Banks are key players in credit markets. Expansionary monetary policy increases bank reserves and loan availability, encouraging investment and consumption. This channel relies on the unique role of banks in solving asymmetric information problems in credit markets, the monetary policy effect is (Mishkin, 2013, p.613):

$$\text{Bank reserves} \uparrow \Rightarrow \text{bank deposits} \uparrow \Rightarrow \text{bank loans} \uparrow \Rightarrow I \uparrow \Rightarrow Y^{ad} \uparrow$$

4.2.2. Balance sheet channel

Financial frictions affect external financing. A firm’s net wealth impacts its borrowing costs and access to credit. Monetary policy can amplify these effects by influencing asset values and wealth.

4.3. The asset price channel

The asset price channel plays a key role in transmitting monetary policy. An increase in interest rates lowers asset values, reducing household wealth and constraining consumption and business investment. Conversely, a decrease in interest rates stimulates these effects.

4.3.1. The exchange rate channel

The exchange rate channel shows how monetary policy affects currency values: lower interest rates lead to depreciation, while higher rates cause appreciation. In open economies, when domestic interest rates rise above foreign rates, the domestic currency tends to appreciate. «When prices are slow to adjust, this makes domestically produced goods more expensive than foreign produced goods. Net exports fall, as do domestic output and employment, while inflation decreases» (Beyer et al., 2017, p. 14). The impact depends on the economy's openness and exchange rate flexibility. In economies with fixed exchange rates, this channel is less effective, and derivatives play a key role in maintaining currency stability.

4.3.2. Equity price channel

There are two key channels through which equity prices influence the monetary transmission mechanism: Tobin's Q theory and the wealth effect.

4.3.2.1. Tobin's Q Theory

Tobin's Q theory explains how monetary policy impacts the economy by influencing stock market valuations. The Q ratio is the market value of a firm divided by the replacement cost of its capital.

- When Q>1: Firms are valued higher than their capital cost, boosting investment and stock issuance.
- When Q < 1: Firms are undervalued, limiting investment.

Expansionary monetary policy increases liquidity, raising stock prices and Q, which encourages more investment. Lower interest rates further enhance stock market appeal by increasing the value of future dividends, supporting corporate investment.

4.3.2.2. Wealth effects

Economic studies have explored how consumer’s financial wealth affects consumption decisions. Modigliani's life-cycle model shows how individuals adjust saving and spending in response to changes in wealth and anticipated future income. Expansionary monetary policy increases asset prices, boosting household wealth and leading to higher consumption.

4.4. Expectations channel

Future interest rate expectations influence medium to long-term interest rates, shaping economic agent’s investment and consumption decisions. As stated « The ability of the central bank to steer expectations and signal the future course of non-standard measures, has a crucial bearing on the effectiveness of these policies » (Beyer et al., 2017, p. 17).

The transmission of monetary policy can be summarized in the following table:

Table 2.1:Summary of the Transmission of Monetary Policy

Transmission Channels	**Description**
Interest rate	Policy measures have an impact on money market rates, bank funding costs, and saving and borrowing costs.
Exchange rate	Affects price of imports and competitiveness.
Asset price and wealth	Asset prices react to policy changes with implications for wealth due to valuation effects.
Balance sheet and profitability	Policy changes affect private sector balance sheets, net worth, and collateral value.
Bank funding and lending	Policy changes affect bank lending supply and demand.
Expectations	Influence private sector long-term expectations including by signalling the future policy course

Source: The European Central Bank

Section 2: Central Bank and Liquidity Management

Liquidity management is a critical component of financial stability for any institution. It involves ensuring that sufficient cash or liquid assets are available to meet short-term obligations while optimizing the use of funds. In this section, we will explore the key principles, strategies, and challenges associated with managing liquidity effectively.

1. Liquidity management processes by central banks

Liquidity management (LM) refers to the strategies employed by central banks to regulate the volume of bank reserves, thereby steering short-term interest rates in alignment with their primary objective, price stability. This process operates within a structured framework that dictates the selection of tools, operational goals, and ultimate targets. Determining an operational target presents a macroeconomic challenge, as it requires choosing variables that are not only controllable but also meaningfully linked to broader economic indicators (Bindsell, 2004).

LM plays a crucial role in bridging the day-to-day monetary operations of the central bank with the overall economy, primarily through its influence on the yield curve—the difference between long-term and short-term interest rates (Bhattacharyya & Sahoo, 2011). By adjusting the nominal short-term interbank rate, the central bank indirectly affects the real interest rate, contingent on inflation levels. However, while long-term interest rates are less explicitly addressed within this framework, they are fundamental in shaping aggregate demand and inflation. Consequently, the link between liquidity management and the broader economy necessitates an understanding of monetary policy transmission mechanisms and a comprehension of how the policy rate interacts with medium- and long-term interest rates. (Kure et al., 2022, p. 29).

This relationship is grounded in the expectations hypothesis of the term structure, which establishes the link between the policy rate and interest rates of varying maturities.

The hypothesis posits that, assuming no arbitrage opportunities, counterparty credit risk, liquidity constraints, or risk premiums linked to uncertainty over future short-term rates, long-term rates would equal the average of expected short-term rates. This relationship is mathematically expressed as follows (Kure et al., 2022, p. 29):

$$l_t = \frac{1}{2}(s_t + E_t s_{t+n}) + e_{t+1}$$

where $\boldsymbol{l}_{\mathrm{t}}$ denotes the nominal long-term interest rate, and $\boldsymbol{E}_{\mathrm{t}}$ represents the expectation operator based on information available at time t, incorporating the current short-term rate $\boldsymbol{s}_{\mathrm{t}}$ and future expected short-term rates over **n** periods. A rise in long-term rates typically signals a tightening of monetary policy and vice versa.

An alternative expression of the equation is as follows (Kure et al., 2022, p. 30):

$$Es_{t+n} - s_t = 2(l_t - s_t) + e_{t+1}$$

Indicating that the slope of the yield curve reflects market expectations regarding the future trajectory of the short-term policy rate. The validity of the expectations hypothesis is tested by assessing the significance of the spread coefficient in this equation.

In an economy where inflation dynamics follow a Phillips curve framework (Kure et al., 2022, p. 30):

$$\pi_{t+1} = \pi_t + v_y y_t + b_z z_{t+1} + e_{t+1}$$

Inflation expectations are shaped by past inflation levels, the output gap, external factors anticipated by the central bank, and an error term. The output gap, defined as:

$$y_{t+1} = v_y y_t + rer + b_z z_{t+1} - q_i i_t + \lambda_{t+1}$$

is influenced by previous output levels, the real exchange rate ($\boldsymbol{rer}=\boldsymbol{e}-\boldsymbol{\pi}$) , external factors, and the real interest rate ($\boldsymbol{ibr}= \boldsymbol{i}_t - \boldsymbol{\pi}_t$).

Monetary policy adjustments follow the Taylor rule:

$$s_t = f(\pi_t, y_t)$$

Which ties policy rate changes to inflation expectations and the output gap. Assuming the central bank consistently meets its target rate $\boldsymbol{S}_t = \boldsymbol{i}_t = \boldsymbol{ibr}$, substituting this equation into the previous ones illustrates the broader connection between liquidity management and macroeconomic conditions. By steering short-term interest rates and influencing the term structure through expectations, central banks affect credit supply, broad money expansion, aggregate demand, and inflation. (Kure et al., 2022, p. 31).

2. Monetary policy instruments for liquidity management

Central banks use various monetary policy tools to regulate liquidity, control inflation, and ensure financial stability. Key instruments include interest rate adjustments, reserve requirements, lending facilities, and open market operations (OMO). These mechanisms influence money supply and credit availability, playing a crucial role in economic management (Wuave et al., 2020).

2.1. Conventional monetary policies

These instruments allow the central bank to influence banking liquidity without directly imposing a credit volume. It primarily acts through the discount rate, mandatory reserves, and open market operations.

2.1.1. Rediscounting

Rediscounting is a refinancing instrument that allows second-tier banks to borrow liquidity directly from the Central Bank. These loans are granted through high-quality private or public securities held in their portfolio, at a price known as the rediscount rate.

This rate serves a dual purpose (Regulation No. 2009-02, 2009.):

- It acts as the official refinancing rate for banks, ensuring them a predetermined profit in exchange for the securities they present.

- It functions as a benchmark credit rate, influencing the cost of financing granted to the economy. An increase in the rediscount rate leads to higher borrowing costs, prompting banks to adjust their lending conditions.

Although rediscounting enables monetary authorities to regulate the money supply, it has certain limitations:

- Access is restricted to specific high-quality securities and subject to caps.
- The rediscount rate is unilaterally set by the Central Bank.
- Its effectiveness is reduced when banks have excess liquidity, particularly in the case of large inflows of foreign capital.
- It does not allow for strict control of the money supply, as the Central Bank cannot refuse to rediscount eligible claims.

Thus, while rediscounting remains a key monetary policy tool, its effectiveness depends on market conditions and the ability of authorities to regulate its use.

2.1.2. Open market operations (OMO)

Open Market Operations (OMO) are a core tool of monetary policy, enabling central banks to regulate liquidity in the money market, control interest rates, and address the refinancing needs of the banking sector (Regulation n°2009-02, 2009). These operations involve the buying or selling of eligible securities and can have maturities ranging from seven days to twelve months. By purchasing securities, the Central Bank injects liquidity into the banking system, allowing banks to expand lending and meet withdrawal demands. Conversely, the sale of securities absorbs excess liquidity, helping to contain inflation and stabilize financial markets (Wuave et al., 2020).

OMO operations typically involve three main instruments:

- **Temporary sales** (including repurchase agreements and secured lending).
- **Outright transactions (Firm operations)** for liquidity injections or withdrawals.
- **Liquidity absorption operations (Unsecured deposits)**, allowing banks to place deposits with the Central Bank without collateral.

OMO is particularly effective during periods of financial instability, as it offers immediate liquidity and signals the Central Bank's commitment to economic stability (Mochebelele, 2020). However, its effectiveness depends on market conditions, as challenges like the limited availability of government securities and underdeveloped secondary markets can constrain its impact (Mutarindwa et al., 2020).

2.1.3. Standing facilities

Standing facilities are mechanisms established by the Central Bank to provide or withdraw liquidity from banks. These operations are initiated by the banks themselves and fall into two main types:

2.1.3.1. Marginal lending facility

The marginal lending facility allows banks to obtain very short-term liquidity (24 hours) from the Central Bank in exchange for eligible collateral. Any bank meeting the eligibility criteria can access this facility. Requests must be submitted no later than 30 minutes before the closing of the ARTS payment system[3] on business days (Regulation No. 2009-02, 2009).

There is no limit on the amounts that can be obtained, provided the bank presents sufficient eligible collateral. Liquidity is provided in the form of overnight repurchase agreements involving eligible negotiable public securities and/or eligible private securities. The loan is repaid the next business day upon the opening of the ARTS payment system and if applicable, the securities settlement system (Regulation No. 2009-02, 2009).

The interest rate applied to the marginal lending facility is set by the Central Bank. It is determined with reference to the main refinancing operations rate, plus a margin, and is announced in advance.

2.1.3.2. Overnight deposit facility

The overnight deposit facility allows banks to place excess liquidity with the Central Bank in the form of 24-hour deposits. Eligible banks, as defined in Article 2, can access this facility on business days. Requests must be submitted no later than 30 minutes before the closing of the ARTS system (Regulation No. 2009-02, 2009).

Overnight deposits are remunerated at an interest rate set by the Central Bank. This rate is determined concerning the main refinancing operations rate, minus a margin, and is announced in advance. No collateral is required from the counterparty. There is no limit on the amount a bank can deposit under this facility. Deposits mature on the following business day upon the opening of the ARTS system (Regulation No. 2009-02, 2009).

2.1.4. Required reserves

Required reserves refer to the minimum amount that banks must maintain in their account at the Central Bank. These reserves are proportional to the demand and short-term deposits held by banks. Over time, this system has been implemented to regulate banking liquidity by making a portion of central bank money unavailable to banks or, if insufficient, requiring banks to obtain it through refinancing. The objective is to regulate liquidity and reinforce the bank’s dependence on the Central Bank.

The Central Bank sets a reserve requirement ratio (r) on eligible deposits (D), meaning banks must hold a required reserve amount (RO) calculated as follows (Delaplace, 2021, p. 106):

$$\mathbf{RO=D\times r}$$

[3] The Payment and Settlement Systems Committee of the Bank for International Settlements defines a payment system as "a set of means, rules, and procedures ensuring the transfer of funds between system participants." This transfer is conducted based on an agreement between participants and the system administrator (typically the central bank) on an agreed technical basis

When a bank creates money, its deposits increase, leading to higher required reserves. An increase in the reserve requirement ratio forces banks to hold more reserves, reducing available liquidity and increasing their refinancing needs. Conversely, a decrease in the ratio allows banks to free up capital.

Reserve requirements play a crucial role in managing liquidity. By adjusting these requirements, central banks can influence the financial system's liquidity. Increasing the reserve ratio restricts lending, reducing liquidity, while lowering the ratio allows banks to free up capital for lending, stimulating economic activity (Mochebelele, 2020). However, the effectiveness of this approach is dependent on economic conditions. For instance, reducing reserve requirements during downturns enhances liquidity and facilitates recovery, while in inflationary periods, it may exacerbate inflation due to excessive credit expansion. A well-calibrated reserve policy is essential for balancing liquidity management with inflation control. The impact of these measures is also influenced by structural factors, such as the efficiency of banks in allocating additional capital (Mutarindwa et al., 2020).

2.2. Unconventional monetary policies

Central banks turn to unconventional monetary policies when traditional transmission channels—like interest rate cuts—become ineffective, as seen during the Global Financial Crisis (GFC). The crisis disrupted financial intermediation, led to soaring unemployment and falling inflation, and pushed interest rates near zero, limiting conventional policy tools. In response, central banks adopted large-scale, unprecedented interventions. While some tools had historical roots, what made them truly unconventional were their scale, combination, and purpose, placing central banks in a new and more active role in financial markets. (Committee on the Global Financial System [CGFS], 2019, pp. 6–7).

The unconventional monetary policy instruments employed are as follows:

2.2.1. Forward guidance

Forward guidance is a tool used by central banks to communicate their future monetary policy intentions, particularly regarding interest rates. It can be:

- Time-based (linked to a specific date), or
- State-based (dependent on economic conditions like inflation or unemployment).

During crises such as the Global Financial Crisis (GFC) and the COVID-19 pandemic, central banks used forward guidance to reinforce their commitment to keeping interest rates low, reduce uncertainty, and clarify how they would respond to abnormal economic conditions. This helped stabilize expectations and support financial markets (Reserve Bank of Australia, P2).

2.2.2. Quantitative easing (QE)

Quantitative easing (QE), also known as asset purchases, involves central banks buying financial assets, primarily government bonds, from the private sector by creating central bank reserves (not physical money). While this tool has long been part of central bank operations, leading to a significant expansion of central bank balance sheets.

The primary goal of QE is to lower interest rates across the yield curve, especially when policy rates are near the effective lower bound. By purchasing assets, central banks reinforce their forward guidance and encourage investment by pushing investors toward other assets, which can influence asset prices and exchange rates (Reserve Bank of Australia, P2).

2.2.3. Negative interest rates

Negative interest rates were once thought impossible due to the belief in a "zero lower bound," which held that interest rates could not fall below zero. The primary concern was that negative rates would encourage people to hold cash outside the banking system, thereby preventing banks from lending. However, following the Global Financial Crisis, some countries implemented negative policy rates. Despite this, commercial banks typically did not pass these rates on to customers, particularly households and small businesses. This situation gave rise to the idea of an "effective lower bound", suggesting that rates cannot realistically fall further without prompting withdrawals and cash hoarding (Reserve Bank of Australia, P3).

Unconventional monetary policy supports financial stability by providing liquidity to stressed financial markets. However, a potential downside is that the availability of central bank liquidity might reduce the incentive for financial institutions to maintain adequate liquidity buffers, potentially increasing vulnerability during future financial stress. To mitigate this risk, regulators have implemented requirements ensuring that institutions hold sufficient liquidity reserves markets (Reserve Bank of Australia, P6).

3. Central Bank intervention in liquidity shortage

Central banks play a crucial role in managing liquidity shortages within the financial system. The literature on central bank liquidity interventions highlights various mechanisms through which monetary authorities ensure financial stability and maintain market confidence. Schemering & Disyatat (2010), provide an extensive discussion on central bank responses to liquidity shortages, categorizing them into three primary areas: general liquidity shortages, acute liquidity crises at specific institutions and systemic liquidity crises.

3.1. Shortage of central bank liquidity

When central banks face a shortage of reserves within the banking system, their intervention primarily aims to ensure the smooth operation of the payment system and to stabilize interest rates near target levels. If the issue is related to an overall insufficient supply, central banks may use various intervention methods. Typically, the preferred approach is to meet the increased demand for reserves by providing loans in the open market, allowing the market to distribute reserves where they are most needed. Central banks typically avoid penalty rates in these cases, as ensuring a proper reserve supply is a key responsibility. These shortages are often not due to bank mismanagement but to unforeseen increases in liquidity demand, as observed during the 2007 liquidity crisis.

When the shortage is due to the distribution of reserves within the banking system-often caused by payment shocks that leave some institutions unexpectedly short-central banks can offer targeted liquidity support. Standing facilities, which allow banks to deposit or borrow reserves from the central bank at specified rates at the end of the day, are designed to address such short-term issues. These facilities typically provide liquidity on an overnight basis, with penalty rates to maintain market incentives. The presence of standing facilities can also stabilize markets by ensuring bank’s access to funds, even if no actual loans are made.

Regardless of whether the liquidity shortage is systemic or specific to certain institutions, the objective of central bank operations is to minimize the impact on market prices, with the exception of overnight interest rates. These operations are designed to avoid conflict with the central bank's overall policy stance. Additionally, since the loans are short-term and fully collateralized, the risk of credit loss is minimal. The principles behind these operations align with traditional interpretations of Bagehot's guidelines to lend freely to solvent institutions, against good collateral, at a penalty rate, as emphasized by Paul Tucker (2004), who noted that much of what was once discretionary central bank lending has now become "hard coded" into the operational framework.

However, the recent financial crisis has revealed several challenges with both open market operations and standing facilities. Financial institutions may lack access to acceptable collateral, or they may not have direct access to central bank liquidity. Furthermore, the growth of global capital markets has led to disturbances originating from markets and counterparties outside the central bank's direct reach. During periods of heightened uncertainty, when financial institutions lose confidence in counterparties, access to standing facilities can become stigmatized, reducing their effectiveness. This was evident during the 2007-2008 crisis when market rates sometimes exceeded the interest rates offered through central bank facilities. In response, central banks have broadened the range of eligible assets, expanded the pool of institutions eligible for direct transactions, and worked to reduce the stigma associated with borrowing from standing facilities.

3.2. Acute shortage of funding liquidity at specific institutions

When a financial institution faces an acute shortage of funding liquidity, intervention by the official sector is necessary if the failure of the institution threatens the stability of the entire financial system. In such cases, the solvency of the institution becomes secondary. Central banks are then faced with the decision of whether to use discretionary authority to provide emergency lending. This situation is distinct from a short-term liquidity shortage where standing facilities may be used, as it involves a larger and potentially prolonged liquidity gap that cannot be addressed by these facilities. Emergency lending can be separated from monetary policy decisions.

In such instances, any liquidity support extended by the central bank can expose it to credit risk, as institutions in need of emergency loans typically no longer have marketable assets or acceptable collateral. The assets pledged for collateral could be part of the borrowing institution's loan book, illiquid securities, or physical assets with uncertain value. If the emergency loan is seen as a form of bridge financing while a takeover or restructuring is arranged, it is usually accompanied by a plan for private sector or government support, such as was the case with Bear Stearns or Northern Rock. This approach is designed to limit the central bank’s potential losses.

The extent of emergency lending depends on the central bank's ability to absorb potential losses. The crisis has revealed that, as financial institutions have globalized, the scope of support required can be vast, necessitating joint participation from fiscal authorities. In extreme cases, such as Iceland in 2008, the demands on the official sector can exceed available resources. Due to moral hazard concerns, officials are cautious in granting such loans, often charging high interest rates to reduce taxpayer exposure and in some cases, imposing conditions such as writing down shareholder equity or replacing management.

Furthermore, the provision of liquidity support in this context is discretionary, meaning that it is not guaranteed, thus preventing the market from assuming it will always be available. This "constructive ambiguity" ensures that the market does not take liquidity support for granted. However, Taylor (2009) argues that the uncertainty surrounding what the government would do and under what circumstances was a key factor contributing to the crisis.

Once emergency loans are granted, effective communication becomes critical. Public announcements can either reassure market participants, thereby boosting confidence, or they can reinforce fears of institutional failure, potentially damaging the institution's reputation further. In the case of Northern Rock in 2007, the announcement of liquidity support from the central bank led to a retail deposit run, only halted by the government guarantee. This created a reluctance among other banks to access central bank facilities, fearing reputational damage, which further tightened money market conditions.

While stigma may not be a concern for an institution that is in clear distress, granting emergency lending could worsen the stigma associated with borrowing from the central bank, complicating future liquidity management. Confidentiality is important to mitigate panic, but it is difficult to maintain in practice, as banks are often aware of the condition of their competitors and large-scale operations typically require public oversight.

4. The role of digital innovation in liquidity management

Advancements in financial technology, including digital banking and fintech solutions, are transforming liquidity management in various countries. Digital platforms facilitate greater financial inclusion by enabling banks to engage with previously unbanked populations, thereby increasing deposit volumes and improving overall liquidity. Additionally, fintech collaborations introduce innovative payment solutions, such as mobile transactions, which enhance cash flow efficiency within the economy. Nevertheless, integrating these digital financial services with conventional banking systems necessitates strong regulatory frameworks and infrastructure improvements, areas where many financial sectors continue to develop (Gumel & Chivurre, 2024).

Managing liquidity in dynamic economic environments remains a complex challenge. Central bank strategies, including monetary policy adjustments, open market operations, and liquidity support measures, play a vital role in maintaining financial stability. However, their impact is often constrained by structural limitations such as foreign reserve shortages, exchange rate fluctuations, and evolving regulatory frameworks. Strengthening regional financial cooperation and accelerating digital transformation could offer viable solutions, yet these approaches require well-coordinated policies and sustained investment in financial infrastructure (Gumel & Chivurre, 2024).

5. The role of liquidity forecasting in central bank liquidity management

Liquidity forecasting plays a fundamental role in central bank operations, ensuring financial stability and enhancing the efficiency of monetary policy. The concept of liquidity, broadly defined, includes all elements of a central bank's liabilities that facilitate economic transactions, such as currency in circulation, bank reserves, and intra-day fund transfers. However, in a stricter sense, liquidity is often limited to commercial bank's deposits held at the central bank (CBWAS, 2012).

Accurate liquidity forecasting enables central banks to determine the appropriate level of liquidity injection or withdrawal from the market. This process helps smooth undesirable fluctuations that could undermine monetary policy effectiveness or cause financial instability. The CBWAS, for instance, relies on weekly balance sheet data to conduct liquidity forecasts, ensuring that monetary policy interventions are well-calibrated to prevailing market conditions (CBWAS, 2012).

Several objectives are associated with liquidity forecasting. Firstly, it facilitates the management of interbank market interest rates. When central banks accurately predict liquidity needs, they can influence short-term interest rates, aligning them with policy goals. Secondly, effective liquidity forecasting reduces credit, market and liquidity risks that could impact the balance sheets of both central banks and commercial banks. A well-functioning money market, supported by precise forecasts, minimizes systemic risks and enhances financial system resilience. Lastly, the credibility of central banks is strengthened when liquidity forecasts are reliable, as they enable efficient open market operations, ensuring the smooth functioning of banking activities (Bindseil, 2000).

According to Bindseil (2000) central bank liquidity forecasts plays a critical role in the effective implementation of monetary policy. In his analysis, Bindseil (2000) examined the accuracy of liquidity forecasts and their impact on the overnight interest rate, emphasizing that accurate predictions contribute to better control of short-term interest rates. Furthermore, the effectiveness of monetary policy depends on the central bank's ability to anticipate and manage liquidity fluctuations, which in turn impacts the transmission of policy measures to financial markets.

In conclusion, liquidity forecasting remains a vital tool for central banks in managing financial stability and policy implementation. The precision of such forecasts directly affects market expectations, monetary policy transmission, and overall financial stability, underscoring the need for continuous improvements in forecasting models and methodologies.

6. Principles of bank liquidity forecasting

Liquidity forecasting involves analyzing data from the central bank's balance sheet. This process consists of estimating the evolution of balance sheet items over a given time horizon. Banks require liquidity to meet their settlement obligations and comply with the reserve requirements set by the central bank. Therefore, the demand for liquidity (DL) corresponds to bank reserves (BR), which are composed of required reserves (RR) and excess reserves (RX) (CBWAS, 2012).:

$$DL_t = BR_t = RR_t + RX_t$$

On the other hand, the supply of liquidity (SL) is determined by the autonomous liquidity position (ALP), which is beyond the direct control of the central bank, and by credit to banks (loans and open-market operations), which are regulated (CBWAS, 2012).:

$$ALP_{\mathrm{t}} = NFA_{\mathrm{t}} + NGP_{\mathrm{t}} - CIC_{\mathrm{t}} - DIV_{\mathrm{t}}$$
$$SL_{\mathrm{t}} = ALP_{\mathrm{t}} + CB_{\mathrm{t}}$$

Liquidity forecasting focuses on two main aspects. The first is identifying the factors that influence changes in bank reserves (BR) and the autonomous liquidity position (ALP). The second involves selecting the most appropriate methods to predict these variations. Since balance sheet projections are typically conducted over a short-term horizon, often on a weekly basis, commonly used forecasting techniques. The results may then be adjusted based on expert judgment and past forecasting errors. This combination of statistical models and human expertise helps produce more reliable estimates (CBWAS, 2012).

Once the components of liquidity supply and demand are estimated, the central bank's interventions are determined by the balance between these two elements. In case of a deficit, the central bank injects liquidity, whereas in case of surplus, it withdraws liquidity. These adjustments are carried out through bank lending and open-market operations to ensure monetary market stability. The equilibrium between liquidity supply and demand can be expressed as follows (CBWAS, 2012):

$$LO_{\mathrm{t}} = DL_{\mathrm{t}}$$
$$DL_{\mathrm{t}} = ALP_{\mathrm{t}} + CB_{\mathrm{t}} = NFA_{\mathrm{t}} + NGP_{\mathrm{t}} - CIC_{\mathrm{t}} - OTHERS_{\mathrm{t}} + CB_{\mathrm{t}}$$
$$CB_{\mathrm{t}} = (RR_{\mathrm{t}} + RX_{\mathrm{t}}) - (NFA_{\mathrm{t}} + NGP_{\mathrm{t}} - OTHERS_{\mathrm{t}} - CIC_{\mathrm{t}})$$

Most existing studies focus on forecasting currency in circulation (CIC) using statistical models, particularly ARIMA models and structural time series models. Harvey et al. (1997) introduced nonlinear approaches to quantify calendar and seasonal effects on money demand. Cabrero et al. (2009) compared the performance of ARIMA models and structural time series models for forecasting CIC in the Eurozone and showed that combining multiple models improves forecasting accuracy. El Hamiani-Khatat (2018) studied short- and long-term money demand and concluded that long-term money demand depends on macroeconomic factors, while short-term demand is dominated by recurring seasonal patterns. Hlaváček et al. (2005) compared a neural network model with a RegARIMA model for CIC forecasting in the United States and found that the neural network was slightly more effective but tended to overreact to rare events such as holidays. Koziński et al. (2015) in Poland, Ikoku (2014) in Nigeria used RegARIMA to model CIC, incorporating recurring events, seasonal effects and holidays.

Forecasting the net government position (NGP) presents additional complexities due to its dependence on fiscal policies and budgetary decisions. Gray (2008) outlined a general framework for forecasting autonomous factors, emphasizing the importance of monitoring government cash flows. However, the study did not provide detailed quantitative models for NGP forecasting. Williams (2010) acknowledged that forecasting government cash balances remains a significant challenge and emphasized the necessity of cooperation with treasury and revenue departments to improve accuracy. Iskandar et al. (2018) explored ARIMA, neural networks and hybrid models to predict government expenditures in Indonesia, making it one of the few studies addressing non-monetary autonomous factors.

Net foreign assets (NFA) represent another critical component in liquidity forecasting. Their fluctuations are often influenced by external factors, such as foreign exchange interventions and economic shocks. Gray (2008) identified NFA as an important autonomous factor, particularly in fixed exchange rate regimes, where central banks intervene to stabilize currency values. The unpredictability of foreign exchange transactions introduces further complexities in NFA forecasting. The GARCH family of models, including standard GARCH, eGARCH, and gjrGARCH, has been widely applied to estimate NFA volatility, capturing asymmetric shocks that affect liquidity supply. (Panagiotelis & Veyrune, 2022).

Despite the importance of these factors, most studies have focused exclusively on CIC, often neglecting NGP and NFA. Furthermore, few models integrate all three components to generate a comprehensive liquidity forecast. Many approaches remain highly country-specific, limiting their generalizability. It proposes a unified framework for forecasting CIC, NGP, and NFA by evaluating different forecasting techniques, such as ARIMA, ETS, TBATS, and GARCH. It also introduces hierarchical reconciliation methods to enhance forecast accuracy, ensuring adaptability across different economic environments (Panagiotelis & Veyrune, 2022).

Liquidity forecasting is crucial in central bank operations and monetary policy implementation. While extensive research has been conducted on CIC forecasting, fewer studies have examined the combined impact of NGP and NFA. It bridges the existing research gap by offering an integrated forecasting methodology and assessing various models to improve prediction accuracy (as cited in Lafarguette et al., 2024).

Section 3: Previous studies on liquidity management

This section presents a review of previous studies, focusing on liquidity management and the role of forecasting in financial decision-making. It highlights how past research has addressed the key objectives and mechanisms involved in managing liquidity effectively.

Javier García-Cicco and Enrique Kawamura (2014) develop a theoretical and quantitative macroeconomic model to analyze the effects of unconventional monetary policies in their paper *Central Bank Liquidity Management and "Unconventional" Monetary Policies*. The study focuses on the Central Bank of Chile’s policies between 2008 and 2011, particularly sterilized foreign exchange interventions and the expansion of eligible collateral for discount window operations.

The authors construct an infinite-horizon, discrete-time model that includes four agents: households, firms, banks, and the central bank. The economy features two consumption goods, one domestically produced and one imported, while firms require bank financing to cover input costs before production. The baseline model captures conventional monetary policy under an inflation-targeting regime, incorporating money market operations through central bank bond transactions.

To extend their analysis, the authors modify the model to assess the macroeconomic impact of sterilized interventions and collateral expansion. Their findings indicate that sterilized interventions can significantly influence output and inflation, with their effects depending on how the central bank manages the additional liquidity generated. Likewise, relaxing collateral requirements supports economic activity but leads to short-term inflationary pressures.

The results show that both policies had a temporary expansionary effect on the economy. Specifically, the impulse responses indicate that inflation increased for a short period but returned to the steady-state level within a year, while output and consumption remained above their steady-state levels for nearly two years. This suggests that the Central Bank of Chile’s use of multiple policy tools helped stabilize the economy during the 2008 financial crisis without compromising its inflation-targeting framework. Moreover, the study highlights that using a combination of unconventional monetary policies is more effective than relying solely on traditional tools like the Taylor rule, as single-policy interventions tended to result in more persistent inflationary pressures.

However, a key limitation of the model is the assumption that liquidity constraints are always binding. While this simplifies computation, it may not fully capture real-world dynamics.

Bindseil (2000) explores the framework of central bank liquidity management, emphasizing three key elements that shape the day-to-day implementation of monetary policy. The first element is the menu of monetary policy instruments, which is directly determined by the central bank. These instruments allow the central bank to manage liquidity in the financial system by supplying or withdrawing funds as needed. The second element is the reserve requirement system, which also falls under the central bank’s control. This system dictates how banks must hold reserves, influencing their liquidity needs and interbank market activities.

The third element consists of the institutional features of the interbank money market, which determine how liquidity is distributed among banks. While the central bank does not directly control this element, it plays a crucial role in shaping the transmission of monetary policy. Bindseil assumes that central banks have efficient tools at their disposal to adjust liquidity levels as needed, without delving into the technical details of these instruments.

The study highlights that the structure of reserve requirements and imperfections in the interbank market significantly impact liquidity management. The ability of central banks to fine-tune liquidity depends on their operational framework and how well they integrate liquidity management with broader monetary policy objectives. Bindseil suggests that developing a comprehensive theory of liquidity management would enhance understanding of money markets, payment systems, and the overall functioning of central banking.

Raj and John (2020) analyze the strategies employed by central banks to manage short-term interest rates in the context of structural surplus liquidity, drawing on the experiences of the Federal Reserve (Fed), the European Central Bank (ECB), and the Reserve Bank of India (RBI). Their study investigates how these institutions have adapted their monetary policy frameworks to retain effective control over short-term rates, despite persistent excess liquidity in the financial system.

The study uses a diverse dataset covering different time periods for each central bank. For the Federal Reserve, the authors consider data from the post-2008 financial crisis era, specifically focusing on the transition to a floor system where interest rates are influenced by administered tools such as the Interest on Excess Reserves (IOER). The ECB's analysis spans the period of unconventional monetary policies following the sovereign debt crisis, assessing how its targeted longer-term refinancing operations (TLTROs) and negative interest rate policies impacted liquidity conditions. For the RBI, the study evaluates data from 2016 onwards, a period characterized by persistent liquidity surplus due to demonetization and large-scale open market operations.

The authors employ various econometric models to analyze the impact of surplus liquidity on interest rate dynamics. A Vector Autoregression (VAR) model is used to estimate the relationship between liquidity surplus and key policy rates such as the federal funds rate (US), the Euro short-term rate (€STR), and the Weighted Average Call Rate (WACR) in India. In addition, a threshold model is applied to capture non-linear effects, showing that beyond a certain liquidity level, additional reserves have a diminishing impact on short-term interest rates.

The results highlight key differences across central banks. In the US, the study finds that the Fed's floor system has been effective in steering interest rates despite high reserves, with a stable spread between the IOER and market rates. The ECB's negative interest rate policy, however, has led to significant distortions in money markets, including declining interbank activity. In India, the RBI's liquidity framework reveals a threshold effect, where surplus liquidity below INR 4.4 trillion reduces the WACR, but beyond this level, additional liquidity has a negligible impact.

The study concludes that while a floor system can provide effective interest rate control, the presence of large structural surplus liquidity requires careful calibration of policy tools. The authors emphasize the importance of adjusting liquidity management frameworks to account for evolving market conditions and regulatory constraints

Kure et al. (2021) investigate the effectiveness of liquidity management instruments by analyzing the relationship between the interbank rate and key monetary policy factors. Using monthly data from December 2007 to December 2020, the authors model the interbank rate's sensitivity to the monetary policy rate (MPR), discretionary liquidity (DL), excess reserves (ER), and autonomous liquidity (AL). The findings reveal a long-run relationship between the interbank rate and liquidity factors, though short-run effects are insignificant. The adjustment to long-run equilibrium is rapid, highlighting the efficiency of policy mechanisms.

The study confirms the presence of a long-run relationship between the interbank rate and liquidity factors, while the short-run relationship appears to be insignificant. However, the adjustment toward the long-run equilibrium is observed to be fast, indicating that changes in liquidity conditions are quickly reflected in the interbank market rates. The findings also highlight that the policy-target rate exhibits both symmetric and asymmetric responses to liquidity factors. Notably, the monetary policy rate and excess reserves demonstrate stronger long-run asymmetry, while the response of discretionary and autonomous liquidity factors remains largely symmetric.

Furthermore, the results indicate that the policy-target rate is more sensitive to monetary contraction than expansion when using the monetary policy rate as a tool. Additionally, the interbank rate reacts more significantly to an increase in excess reserves than to a situation where reserves are scarce, suggesting that managing liquidity by adjusting excess reserves may not be equally effective under different conditions. Despite this, both discretionary and autonomous liquidity factors exert a significant influence on the interbank rate, with their relationship appearing symmetric, potentially due to the specific compartments of the variables considered in the model.

From a policy perspective, the findings confirm that the monetary policy rate is a crucial instrument for liquidity management, with its stronger sensitivity in contraction cycles reinforcing its effectiveness in tightening liquidity conditions. The results also suggest that raising the interbank rate by curtailing excess reserves may be less efficient, as the sensitivity of the policy-target rate to excess reserves varies under different liquidity conditions. Additionally, discretionary and autonomous liquidity factors remain key determinants of the central bank's policy-target rate, emphasizing the need for a comprehensive approach in liquidity management that accounts for both policy-driven and market-driven influences.

Javier Bianchi and Saki Bigio (2014, revised 2017) develop a dynamic equilibrium model to analyze bank's liquidity management and the credit channel of monetary policy. Their study focuses on how banks allocate their assets between liquid reserves and illiquid loans while facing idiosyncratic withdrawal shocks. The central feature of their model is the trade-off between profiting from lending and mitigating liquidity risk by holding precautionary reserves. The model also incorporates the role of the interbank market and central bank policies in influencing bank's liquidity decisions.

The authors calibrate their model using data from the U.S. financial system during the 2006-2007 pre-crisis period. This allows them to capture the regularities of the federal funds market before the financial crisis and assess how banks responded to liquidity shocks. Their framework accounts for institutional details such as reserve requirements and interbank lending mechanisms, making it a suitable tool for evaluating the impact of monetary policy interventions.

Their findings suggest that liquidity risk plays a crucial role in shaping bank's lending behavior and monetary policy transmission. During the 2008 financial crisis, the model indicates that an early disruption in the interbank market led banks to increase their precautionary reserves, which subsequently resulted in a persistent decline in bank lending. The study highlights how monetary policy can influence the liquidity premium, thereby affecting real economic activity.

Beyond its application to the 2008 crisis, the model has broader implications for understanding historical and regulatory issues in banking. The authors discuss how their framework could be used to analyze the Great Depression, particularly the hypothesis by Friedman and Schwartz (2008) that an increase in the deposit-to-currency ratio contributed to the credit crunch. Additionally, the model can be employed to assess the effectiveness of different monetary policy regimes, from the gold standard to modern interest rate targeting, as well as the impact of liquidity regulations on financial stability.

Baldo et al. (2022) investigate how banks manage liquidity in response to the European Central Bank (ECB)'s tiering system, a policy designed to reduce the cost of holding excess reserves. The study explores how banks allocate liquidity among different sources, including money market transactions, internal capital markets within banking groups, and securities holdings, in reaction to this monetary policy change. By analyzing these adjustments, the authors aim to understand how banks balance the costs and benefits of various liquid assets while maintaining financial stability.

The research is based on a sample of monthly bank-level balance sheet data from May 2019 to February 2020, sourced from the ECB's proprietary database. This dataset provides a comprehensive and representative coverage across different jurisdictions and banking models. To assess the impact of the ECB's tiering system, the authors employ a difference-in-differences (DiD) methodology, a standard econometric approach that estimates the average treatment effect of a policy intervention. This model allows the authors to compare banks with high unused tiering allowances (treated group) to those with little to no excess reserve capacity (control group).

The results indicate that banks facing lower reserve costs respond by increasing their reserve holdings, primarily by borrowing more on the money market, reducing net intragroup lending, and decreasing their marketable securities holdings. The study finds that banks prefer maintaining a stable composition of liquid assets over time rather than following a strict pecking order. This suggests that instead of prioritizing one liquidity source over another, they weigh the trade-offs between different liquidity instruments to optimize their balance sheets.

From a monetary policy perspective, the findings highlight that changes in reserve costs, as set by the central bank, create spillover effects across financial markets, particularly the securities markets. The study shows that banks distribute liquidity adjustments across multiple markets, which helps mitigate excessive upward pressure on interest rates. Moreover, the DiD model's results confirm that the tiering system affects bank behavior asymmetrically, with banks below the tiering threshold responding more actively. Furthermore, the stable allocation of liquidity enables central banks to better predict the impact of future monetary policy changes, particularly when adjusting the tiering multiplier or reserve exemption allowances. This underscores the critical role of the ECB's policy framework in shaping bank's liquidity management strategies and ensuring financial market stability.

There is a notable lack of research dedicated to forecasting central bank liquidity or the autonomous factors that influence bank reserves, despite their crucial role in liquidity management. To help fill this gap, we summarize the few existing studies and evaluate various econometric models. The European Central Bank (ECB) conducts studies.

The European Central Bank (ECB), in its research efforts detailed in Working Paper No. 142 (May 2002), aims to evaluate the performance of econometric models in forecasting the weekly circulation of banknotes in the euro area.

Several models were analyzed to predict banknotes in circulation. The two main approaches considered were ARIMA (auto-regressive integrated Moving Average) and STS (Structural Time Series). Additionally, the AGF (Aggregated Forecast) model was assessed, incorporating expert adjustments from national central banks (NCBs).

The empirical results presented in this paper refer to the period January 1994 to February 2001. The dataset consists of weekly observations of banknotes in circulation within the euro area. The study suggests that weekly data, rather than daily observations, would be sufficient for forecasting purposes. These data exhibit strong seasonal patterns, influenced by holiday periods and consumption behavior.

Data were collected from national central banks across the euro area, covering a representative period before and after the introduction of the euro. The evaluation focuses on the accuracy of forecasts and their impact on liquidity management decisions within the ECB.

Results indicate that ARIMA performs better for medium-term forecasts (5 weeks and beyond), whereas STS is more accurate for short-term horizons (1 to 4 weeks). A combination of both models provides the best overall accuracy, suggesting that some seasonal patterns cannot be fully captured by a single approach. Despite their effectiveness, the models struggled to account for exceptional effects, such as those related to the euro transition. Therefore, expert judgment from NCBs remains crucial for refining forecasts.

The Central Bank of West African States (CBWAS) has undertaken research on banking liquidity forecasting, aligning its efforts with the practices adopted by several modern central banks. The data used in this study come from its daily balance sheets, covering the period from January 2008 to December 2011. These data were collected and analyzed to better understand the structure of autonomous factors influencing banking liquidity.

The sample consists of daily observations over several years, providing a robust statistical foundation for the development of forecasting models.

Two types of models were developed: the Rolling Weekly Daily Model (MQGH) and the Global Daily Model (MQG). The MQGH consists of five modules, each corresponding to a working day, allowing for detailed forecasting over a longer horizon. In contrast, the MQG provides a comprehensive estimation and is more suitable for short-term forecasts.

The results indicate that these models outperform the weekly forecasting model, particularly in predicting autonomous liquidity factors. However, improvements are still possible, especially by incorporating additional information on the Net Government Position and optimizing the monitoring of daily financial flows.

A recent master’s thesis by **Fériel Hamza (2023)** conducted an analysis of autonomous factors affecting banking liquidity in Algeria, using weekly data from 2015 to 2022. The objective of the study was to model and forecast the evolution of two key determinants: Net Foreign Assets (NFA) and Currency in Circulation (CIC), in order to better understand their influence on banking liquidity. The dataset consisted of weekly observations over eight years. Two econometric approaches were applied: a multiple linear regression model to examine the relationship between NFA, exchange rates, and oil prices; and a dummy variable model to capture the seasonal behavior of CIC. The findings revealed that an increase in NFA is generally associated with improved banking liquidity, while growth in CIC or Treasury funds tends to reduce it. The CIC model effectively captured its predictable seasonal fluctuations, particularly around salary payment periods. However, the NFA model was limited by the small number of explanatory variables, highlighting the need for future studies to include additional factors, such as hydrocarbon export volumes, for a more comprehensive analysis.

Soleimani (2024) investigates the application of artificial intelligence (AI) in enhancing economic transparency and optimizing liquidity management within financial markets. The study emphasizes how AI technologies, such as machine learning, natural language processing (NLP), and reinforcement learning, overcome the limitations of traditional economic analysis by enabling real-time data processing, predictive accuracy, and dynamic decision-making for central banks and financial institutions. By synthesizing existing research and case studies (e.g., central banks, commercial financial entities), the author highlights AI’s capacity to improve liquidity forecasting, automate regulatory compliance, and reduce information asymmetry through advanced sentiment analysis and pattern recognition in high-frequency trading data. Key contributions include the integration of theoretical frameworks from information economics, Keynesian liquidity preference theory, and computational principles like deep learning (e.g., LSTM networks) to explain how AI aligns liquidity management with macroeconomic stability. Empirical evidence demonstrates AI’s effectiveness in predicting financial crises and optimizing asset allocation. However, the study identifies persistent challenges, including algorithmic bias, data privacy risks, and the "black-box" nature of AI models, which necessitate technical solutions and robust regulatory frameworks. From a policy perspective, the research advocates for an organizational excellence model that combines strategic alignment, data governance, and interdisciplinary collaboration to ensure ethical AI deployment. The findings suggest that AI adoption enables proactive risk management and enhances central bank’s ability to simulate monetary policy impacts, though future work should address its applicability in emerging economies, interactions with complementary technologies, and the development of transnational ethical standards to mitigate systemic risks.

Conclusion of the Second Chapter

The objective of this chapter was to introduce the concept of monetary policy and highlight its connection to liquidity management.

Several key factors have influenced the development of monetary policy over time, encouraging its evolution as a fundamental tool for ensuring economic stability. Central to this policy are its various objectives, such as controlling inflation, stabilizing currency, and fostering economic growth.

In defining these objectives, it is clear that monetary policy acts as both a process and a tool, with the ultimate goal of maintaining financial stability. To fully understand its impact, one must also consider the role of liquidity management, which is integral to ensuring the effective functioning of the financial system.

As we move forward, the next chapter will address the concept of forecasting as an essential element of liquidity management. This approach will help to better anticipate economic shifts and enhance the effectiveness of liquidity control mechanisms.

Chapter III: Forecasting the Liquidity of the Bank of Algeria

Introduction to the Third Chapter

After identifying the main determinants of bank liquidity and examining their behavior within the Algerian financial system, we emphasized the necessity of developing reliable forecasting methods. Anticipating fluctuations in liquidity-related variables is essential for strengthening monetary policy frameworks and ensuring overall financial stability. In light of the growing complexity of financial environments, combining traditional econometric models with modern machine learning approaches offers a promising path to improving predictive accuracy.

In this chapter, we focus on forecasting the primary determinants of central bank liquidity—Net Foreign Assets (NFA), Currency in Circulation (CIC), and Net Government Position (NGP)—by applying both classical statistical models and deep learning techniques. The goal is to evaluate and compare the forecasting performance of these models, with the intention of identifying the most effective approaches for predicting liquidity conditions in Algeria. To achieve this, the chapter is structured as follows:

- **Section 1**: Exploratory data analysis of autonomous liquidity factors.
- **Section 2**: Forecasting Using Classical Models.
- **Section 3**: Forecasting Using Deep Learning Models.
- **Section 4:** Comparison of Forecasting Performance.

Section 1: Exploratory data analysis of autonomous liquidity factors

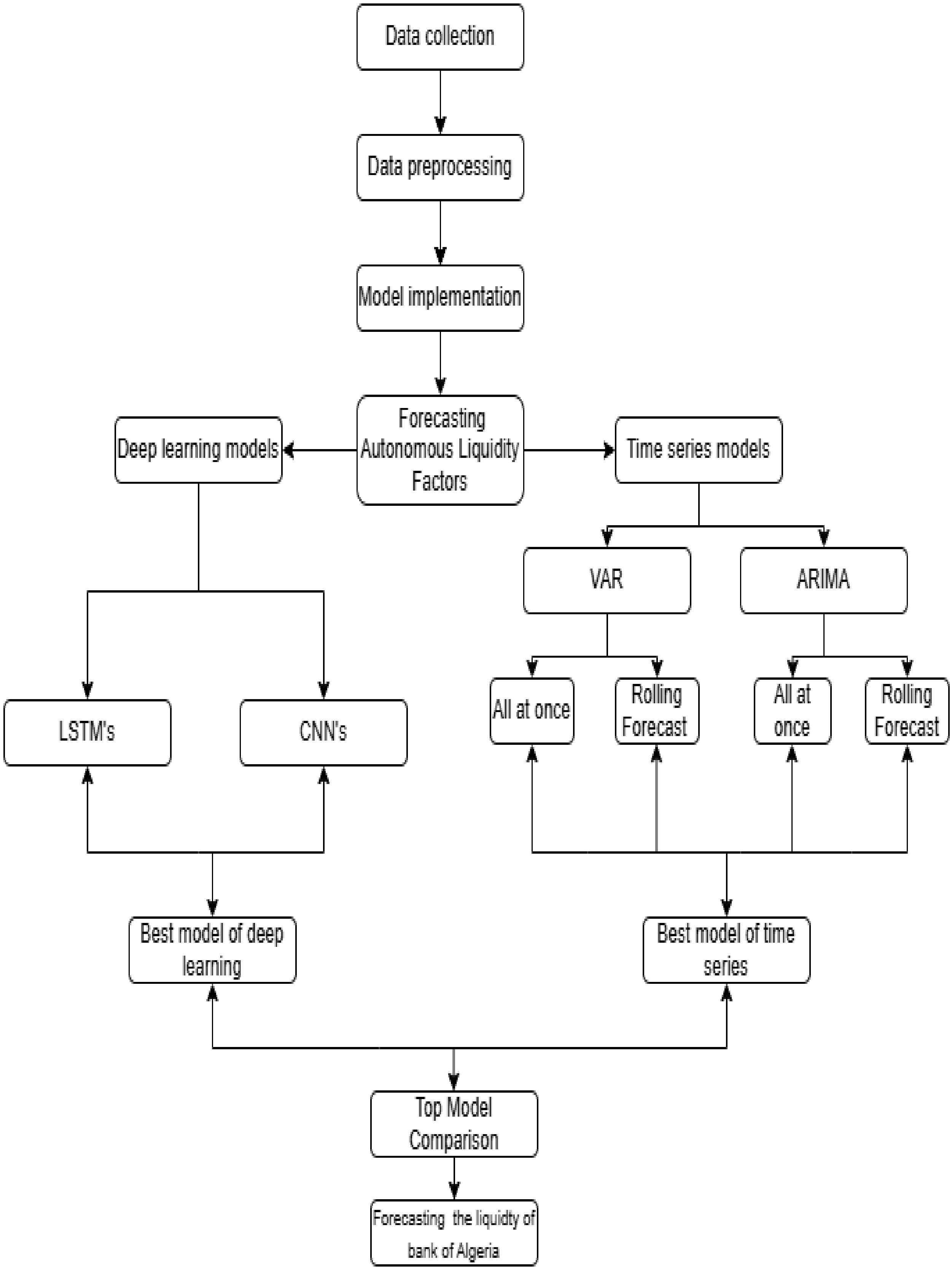
This section presents the descriptive analysis of the dataset collected from the Bank of Algeria. The analysis is based on a series of daily observations covering the period from 2015 to 2023. It focuses on the evolution of the autonomous factors, namely Net Foreign Assets (NFA), Net Government Position (NGP), and Currency in Circulation (CIC), which are key components influencing liquidity. The objective is to summarize the central tendencies and dispersion of these variables to provide an initial understanding of their behavior over time. This dataset, provided by the central bank, offers essential insights into the factors that impact liquidity and serves as a foundation for further analysis.

1. Methodological Approach

In this study, we adopted a quantitative approach based on time series analysis. The data were collected from the Bank of Algeria, which serves as an official and reliable source for macroeconomic indicators. The sample covers the period from 2015 to 2023, with a daily frequency. The variables selected for analysis are: Net Foreign Assets (NFA), Net Government Position (NGP), and Currency in Circulation (CIC). These autonomous factors were chosen due to their key role in influencing banking liquidity.

To better illustrate the different stages of our methodological process, a flowchart has been included. It provides a schematic representation of the steps followed — from data collection to the application of statistical and deep learning forecasting models.

Figure 3.1:Flowchart of the Research Steps



Source: Made by the student

2. Descriptive analysis of autonomous factors

The following table summarizes the descriptive statistics for the key autonomous factors (NFA), (NGP), and (CIC) based on daily data from 2015 to 2023, providing insights into their central tendency and variability.

Table 3.1:Descriptive statistics table for autonomous factors

Unit: billion DZD

Autonomous factors	*NFA*	*NGP*	*CIC*
N	*2346*	*2346*	*2346*
$\overline{x}$	*6,945,614.77*	*1,394,651.77*	*5,403,232.33*
SD	*2,193,814.36*	*936,466.8*	*1,204,000.81*
CV	*31.59%*	*67.15%*	*22.28%*
Sk	*0.38*	*0.85*	*0.45*
KR	*-0.55*	*0,26*	*-1.01*
Min	*3,499,241.66*	*-37,651.6*	*3,550,390.12*
Q1	*5,127,263.76*	*673,362.0*	*4,417,061.64*
Q2	*7,042,842.99*	*1,200,067.2*	*5,073,635.32*
Q3	*8,064,010.08*	*1,829,038.68*	*6,463,631.91*
IQR	*2,936,746.31*	*2,046,570.27*	*1,185,676.68*
Max	*12,635,475.48*	*4,293,147.97*	*7,751,993.43*

Source: generated by the student using Python.

Table 3.1 presents descriptive statistics for three autonomous financial factors: Net Foreign Assets (NFA), Government Net Position (NGP), and Currency in Circulation (CIC), based on 2346 observations. On average, NFA records the highest value (6945614.77), followed by CIC (5403232.33 billion), and NGP at around (1394651.77 billion). This indicates that, over the observed period, the level of net foreign assets is substantially higher than the other two factors.

In terms of variability, the coefficient of variation (CV) shows that NGP exhibits the greatest relative fluctuation (67.15%), suggesting a highly volatile behavior compared to its mean. NFA follows with a moderate variability of 31.59%, while CIC appears the most stable, with a lower coefficient of variation of 22.28%. Therefore, among the three factors, NGP is the least predictable over time, while CIC is the most consistent.

Regarding the shape of the distributions, skewness values are slightly positive for all variables, indicating a mild asymmetry with a tendency toward higher values. The kurtosis values are all negative or close to zero, implying distributions with shorter tails compared to a normal distribution (platykurtic). This suggests fewer extreme values or outliers than would be expected in a normal distribution.

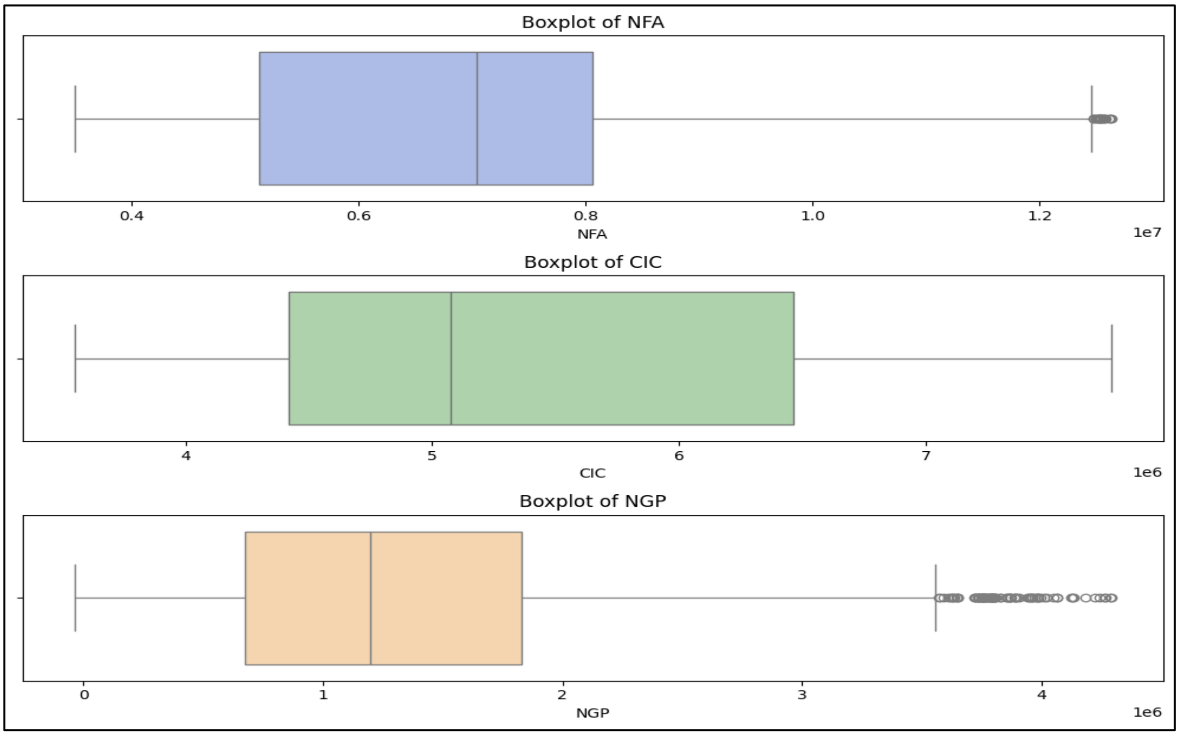
The range of values indicates notable differences among the three variables. NFA shows the highest range, reaching 9,136,234.48 billion, reflecting the widest spread of values. NGP follows with a range of 4,330,799.57 billion, while CIC has the smallest range at 4,201,603.31 billion. These results highlight that NFA experienced greater fluctuations compared to NGP and CIC, with CIC displaying the least variation.

3. Boxplot Analysis

Figure 3.2 shows the boxplots of NGP, CIC, and NFA, which exhibit distinct statistical characteristics in terms of central tendency, spread, skewness, and outlier behavior. The boxplots reveal that CIC has a median closer to the first quartile, indicating a concentration of lower values but no extreme outliers. NFA's median is near the third quartile with several high-end outliers, while NGP's median is also close to the first quartile but with many high-value outliers. Both NFA and NGP display greater variability and stronger right skewness compared to CIC. The interquartile ranges (IQR)[1] further confirm these differences in spread, with NFA (2,936,746.31) and NGP (2,046,570.27) showing much wider middle 50% ranges compared to CIC (1,185,676.68), reflecting their higher variability.

[1] The interquartile range (IQR) is calculated as the difference between the third quartile (Q3) and the first quartile (Q1), capturing the spread of the central 50% of the data.

Figure 3.2: Box Plot of NFA, CIC, NGP



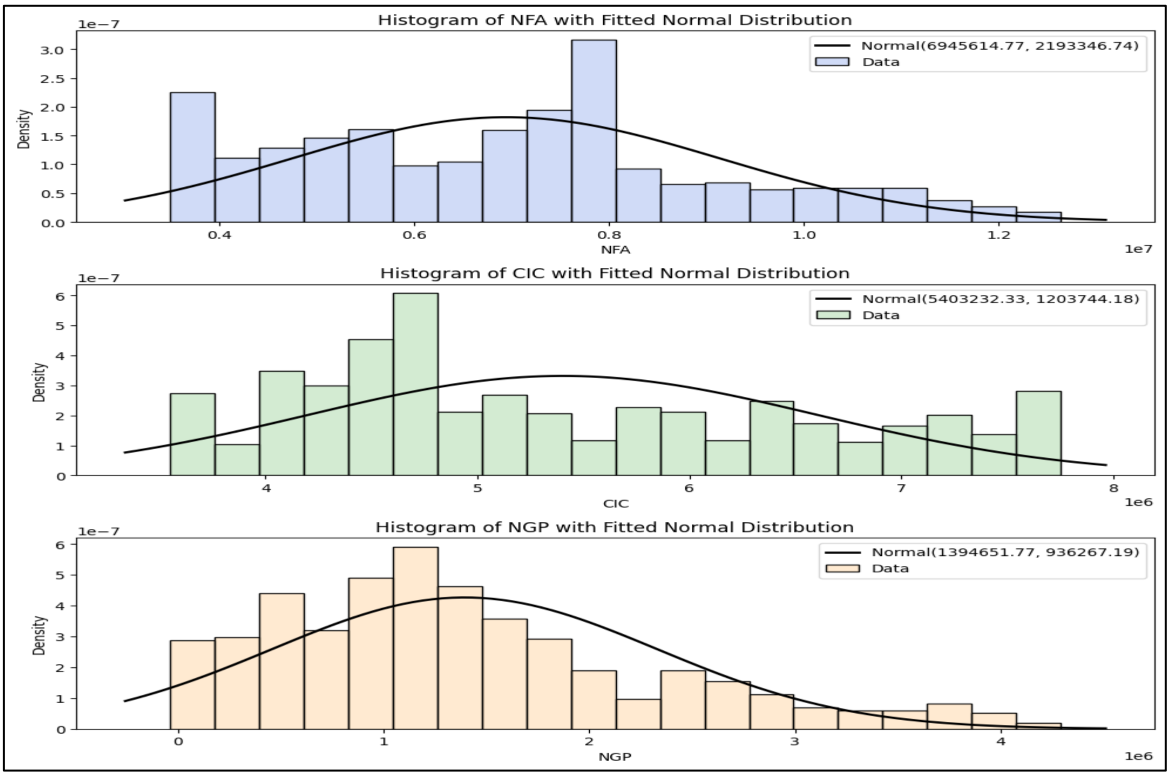
Source: generated by the student using Python.

4. Normality

Figures 3.3 and **3.4** display histograms and Q-Q plots for the NFA, CIC, and NGP datasets, all showing right-skewed distributions. The histograms reveal that NFA and NGP have a concentration of data at lower values, with long tails toward higher values, confirming positive skewness (SK) and potential heavy-tailed behavior. CIC shows a similar concentration at the lower end but with a less pronounced tail, indicating a mild right-skew and moderate kurtosis.

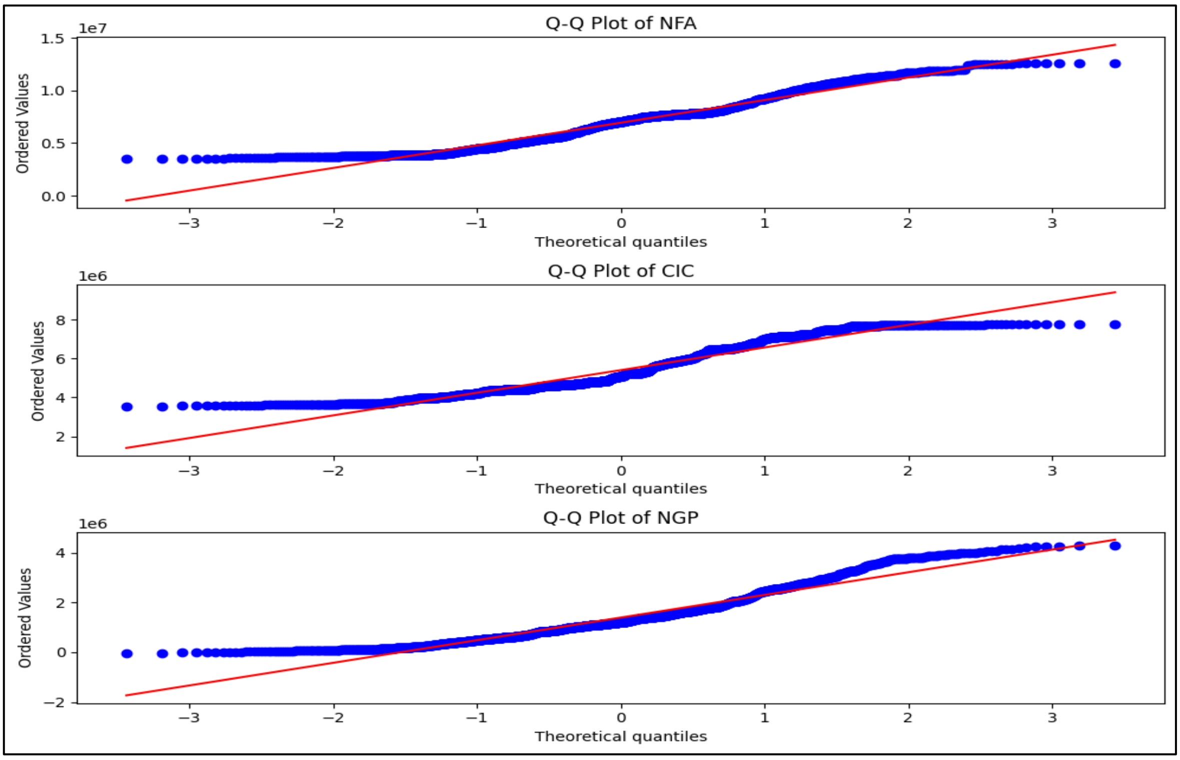
The Q-Q plots confirm these findings, with significant deviations from the reference line in the tails for NFA and NGP, indicating right-skewness and heavy tails. CIC also shows deviations at the extremes, further supporting a slight right-skew. These patterns indicate that all three datasets do not follow a normal distribution, with extreme values appearing more frequently than expected under normality, confirmed by both skewness and kurtosis measures.

Figure 3.3: Histogram of NFA, CIC, NGP



Source: generated by the student using Python.

Figure 3.4: Q-Q Plot of NFA, CIC, NGP



Source: generated by the student using Python.

4.1. Normality Tests

After visual inspections through histograms and Q-Q plots, we will perform statistical tests to confirm the normality of the data. These tests provide a more precise evaluation beyond just visual analysis.

- **Shapiro-Wilk test:**

The Shapiro-Wilk test is a statistical test used to assess whether a sample of data follows a normal distribution. It is particularly useful for checking the normality assumption of residuals in regression models (Das, 2016).

Hypotheses:

- **H_0**: The data follows a normal distribution.
- **H_1**: The data does not follow a normal distribution.

- **Kolmogorov-Smirnov test:**

The Kolmogorov-Smirnov test is used to compare an empirical distribution with a theoretical distribution (such as the normal distribution). It tests whether the sample data follows a given distribution (Das, 2016).

Hypotheses:

- **H_0**: The data follows a normal distribution.
- **H_1**: The data does not follow a normal distribution.

The decision rule for both the Shapiro-Wilk and Kolmogorov-Smirnov tests is as follows:

- Reject the null hypothesis (H_0) if the p-value is < 0.05, which indicates that the data does not follow a normal distribution.
- Fail to reject the null hypothesis (H_0) if the p-value > 0.05, suggesting that the data follows a normal distribution

Test Results:

The results from the normality tests, shown in **Table 3.2**, reveal p-values of 0.0000 for both the Shapiro-Wilk and Kolmogorov-Smirnov tests across all datasets (NGP, CIC, and NFA). Given that these p-values are significantly below the 0.05 threshold, the null hypothesis (H_0) of normality is rejected for each dataset. Consequently, it can be concluded that none of the datasets exhibit a normal distribution.

Table 3.2: Results of Normality Tests

P-Values	***NFA***	***CIC***	***NGP***
Shapiro-Wilk Test	*0.0000*	*0.0000*	*0.0000*
Kolmogorov-Smirnov Test	*0.0000*	*0.0000*	*0.0000*

Source: generated by the student using Python

Section 2: Classical time series models

This section focuses on forecasting Net Foreign Assets (NFA), Net Government Position (NGP), and Currency in Circulation (CIC) using classical time series models, including ARIMA and VAR. The objective is to estimate their future values based on historical data. For this purpose, 80% of the data will be used for training the models, while the remaining 20% will be reserved for testing and evaluating their forecasting performance.

1. Autoregressive Integrated Moving Average (ARIMA) Processes

ARMA processes are assumed to be stationary, which limits their use for non-stationary time series. To address this limitation, we use ARIMA(p,d,q) (*Autoregressive Integrated Moving Average*) models, where p represents the autoregressive order,d represents the differencing order, and q represents the moving average order.These models are expressed as follows (Hyndman & Athanasopoulos, 2021):

$$(1 - \phi_1 B - \cdots - \phi_p B^\rho)(1 - B)^d X_t = (1 - \theta_1 B - \cdots - \theta_q B^d)\ \epsilon_t$$

Alternatively, the equation can be written as:

$$\phi(L)(1 - L)^d X_t = \theta(L)\epsilon_t$$

where L is the lag operator The differencing $(1 - L)^d$ is used to eliminate the trend and make the series stationary.

2. The Box & Jenkins Methodology Steps

The Box & Jenkins methodology is a rigorous and systematic approach to analyzing time series based on their underlying characteristics. This methodology follows a five-step procedure (Box, Jenkins, & Reinsel, 2015):

2.1. Model identification

In this step, the data is transformed, such as through logarithms, to stabilize variance, and differenced if necessary to achieve stationarity, ensuring consistent statistical properties over time.

2.2. Parameters estimations

Model estimation involves finding ARIMA parameters by maximizing likelihood or minimizing errors to best fit the time series for accurate forecasting.

2.3. Diagnostics checking

To validate the adequacy of the model, we apply tests on the residuals in addition to the stationarity test.

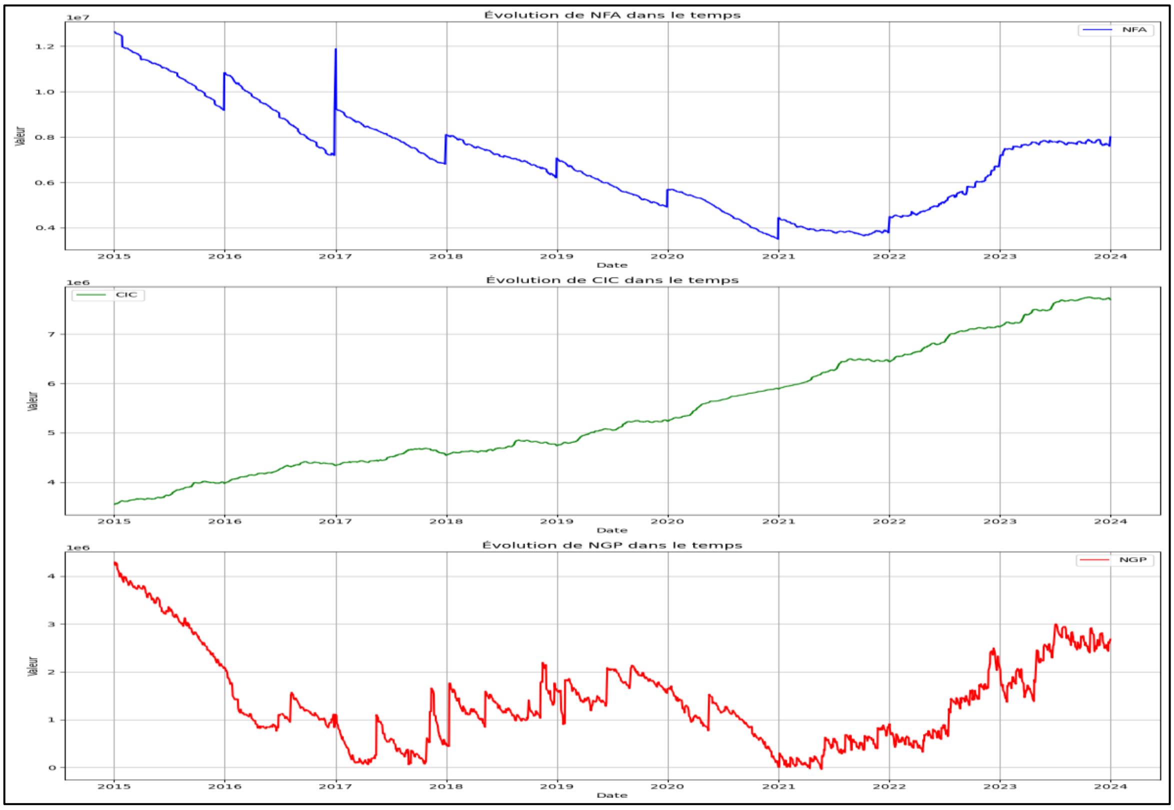
2.4. Forecasting

The final step involves predicting future values using the validated model.

3. Preliminary analysis of the time series

Before conducting any analysis of a time series, it is essential to first examine its graphical representation, as shown in **Figure 3.5.** The NFA series exhibits a clear downward trend until 2021, followed by an upward recovery, with repeated drops occurring at regular intervals, suggesting seasonality. These fluctuations indicate that the series is non-stationary. The CIC series, on the other hand, shows a steady increase over time, without significant changes or seasonal patterns, confirming non-stationarity. Similarly, the NGP series displays high volatility, characterized by frequent peaks and drops, with notable fluctuations confirming non-stationary behavior.

Figure 3.5: Evolution of NFA, NGP, and CIC over time



Source: generated by the student using Python

3.1. Stationary test

Assessing the stationarity of time series data is essential prior to further analysis. Accordingly, three tests were employed: the Augmented Dickey-Fuller (ADF) test, the Phillips-Perron (PP) test, and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test.

➢ For the Augmented Dickey-Fuller (ADF)

- H_0: The series has a unit root (non-stationary).
- H_1: The series is stationary.

If the p-value is less than 0.05, we reject H_0 and conclude the series is stationary. If the p-value is greater than 0.05, we fail to reject H_0, implying the series is non-stationary, and further transformations may be needed (Fuller, 1996).

➢ Phillips-Perron (PP) Test

- **H_0**: The series has a unit root (non-stationary).
- **H_1**: The series is stationary.

If the p-value is less than 0.05, the null hypothesis is rejected, indicating that the series is stationary. If the p-value exceeds 0.05, the null hypothesis cannot be rejected, suggesting that the series is non-stationary (Hamilton, 1994).

➢ For the Kwiatkowski-Phillips-Schmidt-Shin test:

- **H_0**: The series is stationary.
- **H_1**: The series is non-stationary.

If the p-value is greater than 0.05, we fail to reject H_0, indicating the series is stationary. If the p-value is less than 0.05, we reject H_0, concluding the series is non-stationary and requires differencing or transformation for analysis (Gujarati & Porter, 2009).

Applying these tests to the series to confirm the stationarity of the series, we applied the Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests. The ADF and PP tests failed to reject the null hypothesis for the NFA, CIC, and NGP series, as their p-values exceeded the 5% significance level, indicating that these series are non-stationary. In contrast, the KPSS test rejected the null hypothesis of stationarity for all three series, as their p-values were below 5%, further confirming their non-stationarity. After differencing the series, both the ADF and PP tests strongly rejected the null hypothesis of non-stationarity for all three series ($p = 0.000$), confirming their stationarity. However, the KPSS test accepted stationarity for CIC and NGP ($p > 0.05$) but rejected it for NFA ($p = 0.01$). The results of these tests are summarized in **Table 3.3.**

Table 3.3: Results of stationarity tests for the time series before and after differencing

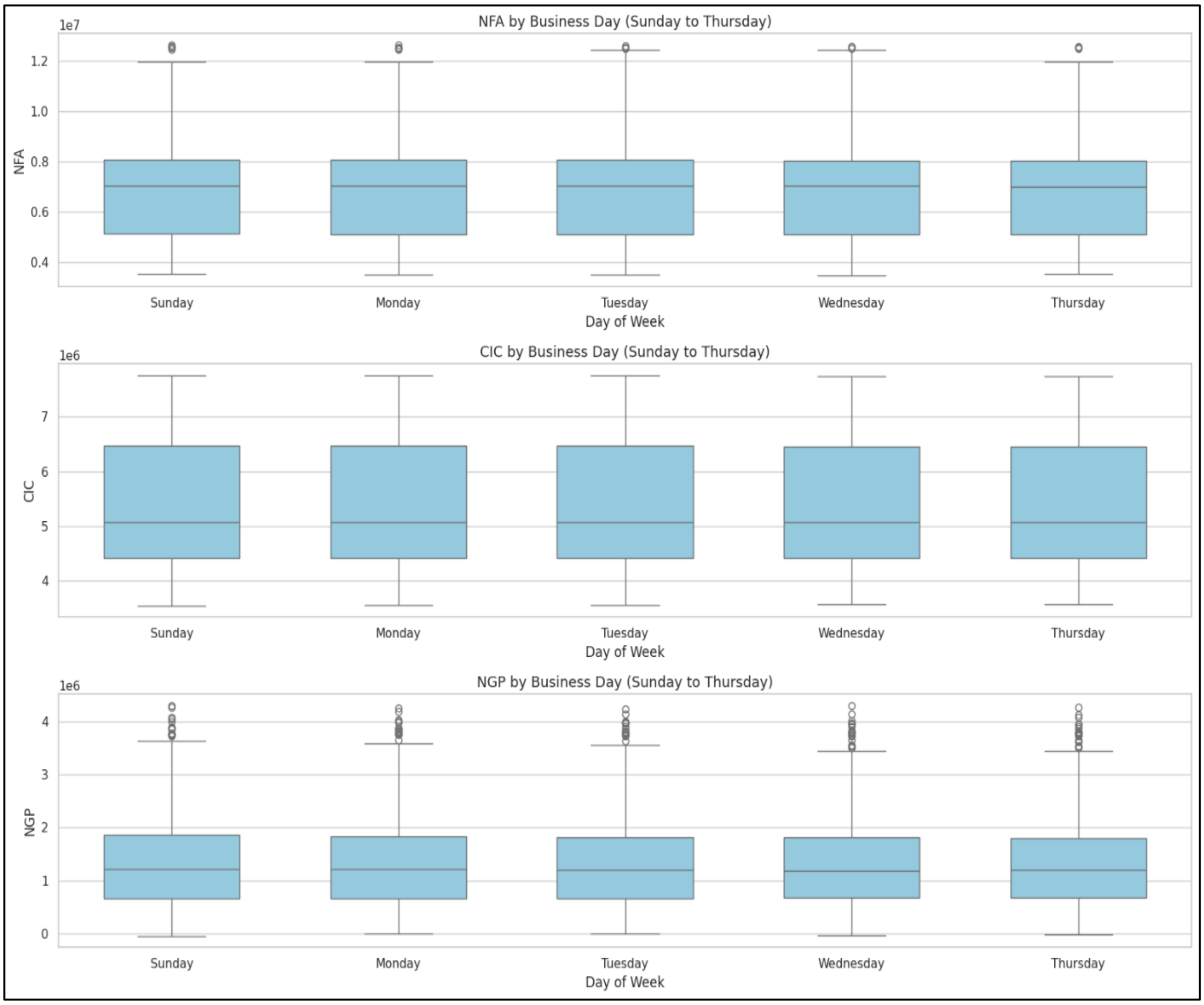
P-Value	*NFA*	*ΔNFA*	*CIC*	*ΔCIC*	*NGP*	*ΔNGP*
ADF	0.066	0.00	0.99	0.00	0.085	0.00
PP	0.07	0.00	0.99	0.00	0.05	0.00
KPSS	0.01	0.01	0.01	0.06	0.01	0.09

Source: generated by the student using Python.

3.2. Seasonality analysis

The box plots show the distribution of NFA, CIC, and NGP across business days from Sunday to Thursday. NFA and CIC have relatively stable medians and spreads, though NFA shows some high outliers. CIC is the most stable, with consistent distributions and no outliers, indicating low volatility and no day-of-week effect. In contrast, NGP is the most variable, with many outliers. Overall, none of the variables display strong day-of-week patterns, as shown in **Figure 3.6**.

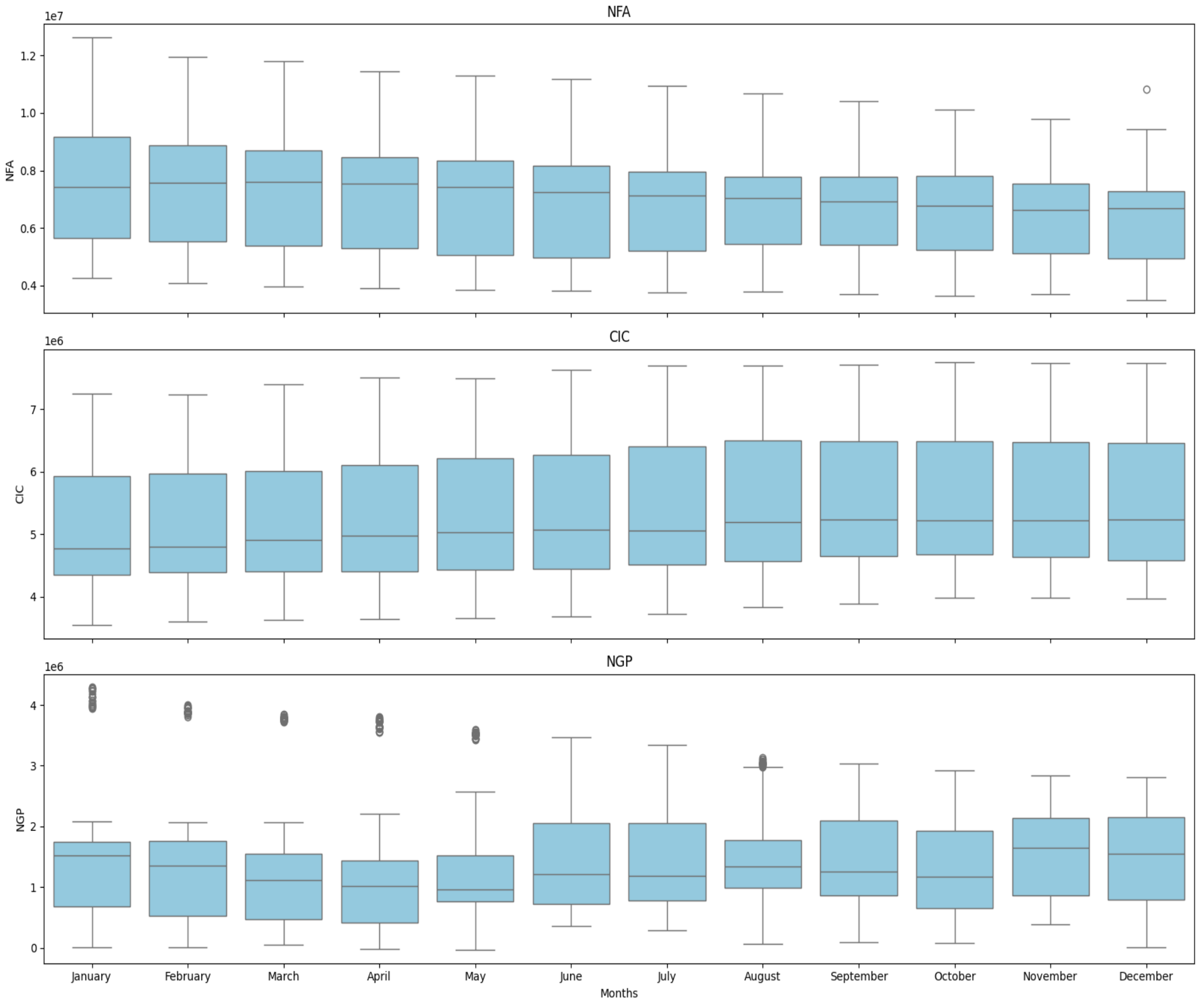
Figure 3.6: Seasonality patterns of time series throughout the Business Day



Source: generated by the student using Python.

The boxplots, as shown **Figure 3.7,** illustrate the monthly distributions of NFA, CIC, and GPN. NFA exhibits a clear downward trend throughout the year, with both median values and interquartile ranges gradually decreasing from January to December, suggesting a systematic reduction in net foreign assets. CIC displays an upward trajectory, with median values and spread increasing steadily across months, indicating growing currency circulation over the year. NGP shows negligible seasonality, with notable fluctuations, lower medians in March-April, rising in June-July, and remaining relatively stable in later months, alongside significant outliers in the first quarter.

Figure 3.7: Seasonality patterns of series throughout the months



Source: generated by the student using Python.

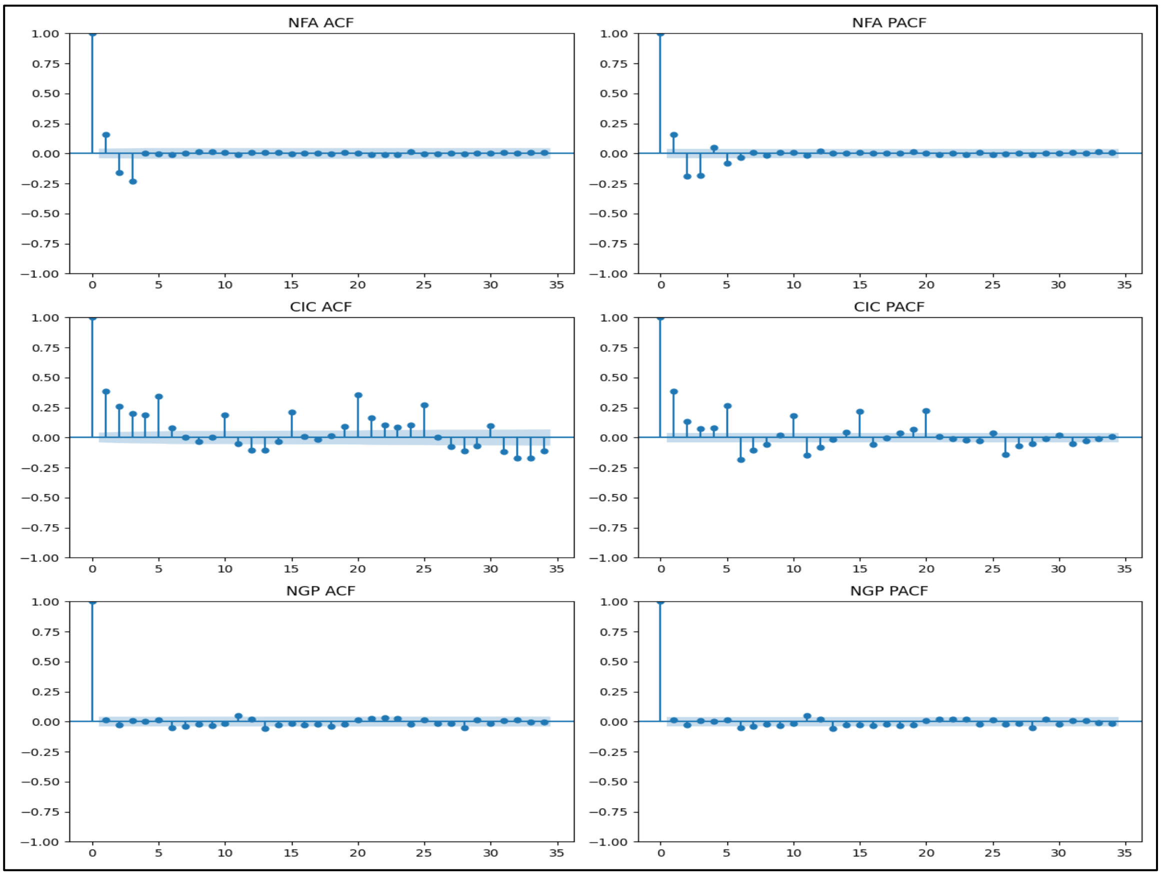
4. Box & Jenkins method on Autonomous Factors

We will apply the Box-Jenkins steps to our time series:

4.1. Model identification

After making all the series stationary, we proceeded with identifying the ARIMA model parameters by estimating the orders p and q using the correlograms of the series (ACF and PACF) to select the most suitable forecasting model for each series **(Figure 3.8).** Upon analyzing the ACF and PACF correlograms for the three series (NFA, CIC, and NGP), we determined the appropriate values for the AR (p) and MA (q) orders. Specifically, for the NFA series, the best model was identified with p = 3 and q = 5, while the values for CIC and NGP were selected in a similar manner. **Table 3.4** presents the selected (p, q) values for each series, which are based on the analysis of the ACF and PACF plots

Figure 3.8: ACF and PACF Correlograms for NFA, CIC, and NGP Series



Source: generated by the student using Python.

Table 3.4: Optimal ARIMA Model Orders (p, q) for Stationary NFA, CIC, and NGP

Serie	***NFA***	***CIC***	***NGP***
Selected model	ARIMA (2,1,1)	ARIMA (1,1,1)	ARIMA (2,1,1)

Source: generated by the student using Python.

4.2. Parameter estimation

The parameters of the ARIMA models for the series NFA, CIC, and GPN are given in Equations, respectively.

$$\boldsymbol{\Delta NFA}_t = 0.5982 \cdot \Delta NFA_{t-1} - 0.0393 \cdot \Delta NFA_{t-2} - 0.5784 \cdot \varepsilon_{t-1} + \varepsilon_t$$

$$\mathbf{\Delta CIC}_t = 1.0000\ \Delta CIC_{t-1} - 0.9999\ \varepsilon_{t-1} + \varepsilon_t$$

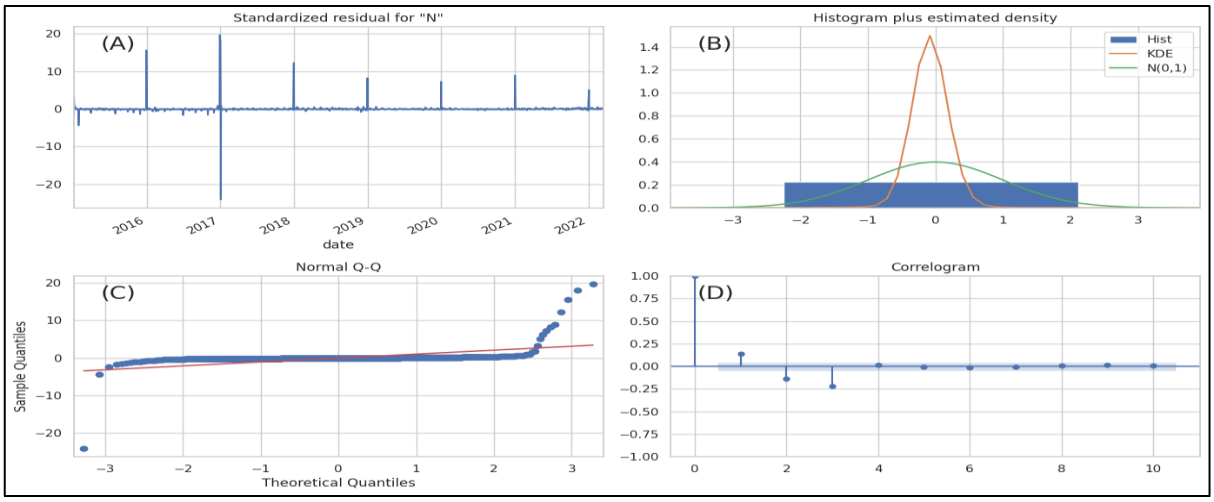
$$\mathbf{\Delta NGP}_t = -0.7666 \cdot \Delta NGP_{t-1} - 0.0200 \cdot \Delta NGP_{t-2} + 0.7636 \cdot \varepsilon_{t-1} + \varepsilon_t$$

4.3. Diagnostic checking

In order to validate the previously estimated models, we will examine the residuals of each series to assess whether they exhibit the characteristics of white noise.

- **NFA:**

Figure 3.9: Graphical Analysis of the Residuals of the NFA Series

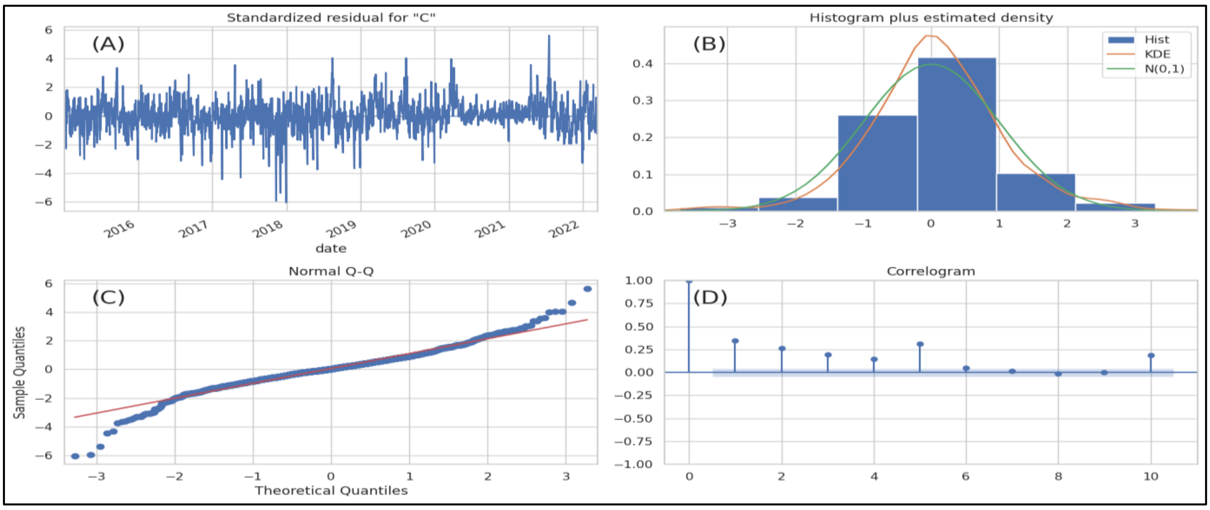


Source: generated by the student using Python.

The residuals of the NFA model show no significant autocorrelation, indicating a good fit in terms of temporal structure. However, visible outliers and deviations from normality suggest the presence of extreme values not fully captured by the model as shown in **Figure 3.9**.

- **CIC:**

Figure 3.10: Graphical Analysis of the Residuals of the CIC Series

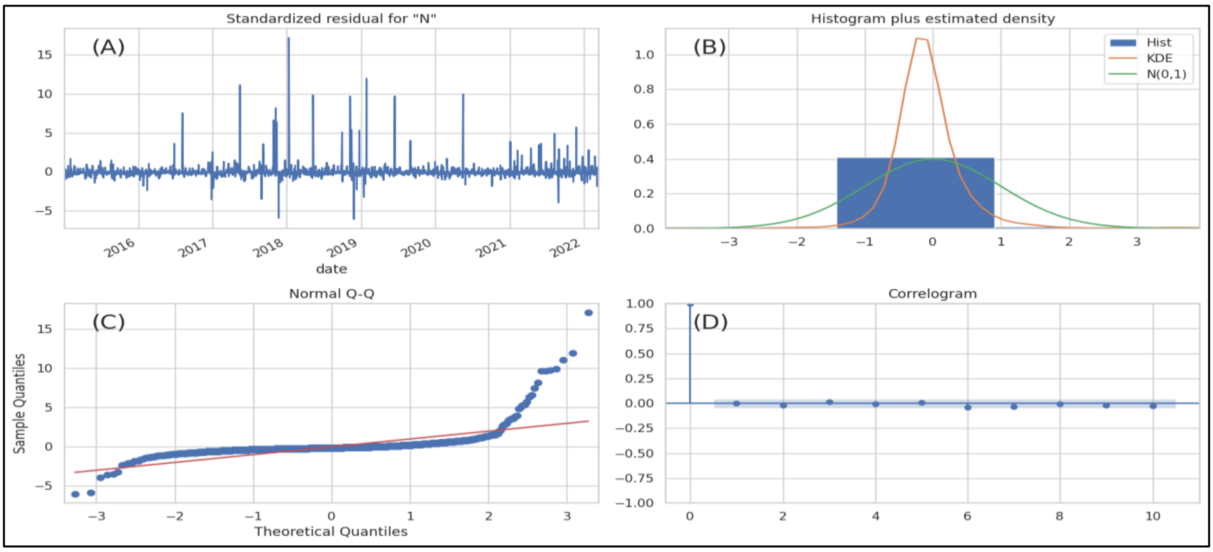


Source: generated by the student using Python.

Figure 3.10 present The residuals for the (CIC) model show mild autocorrelation at initial lags. Additionally, slight deviations from normality and visible outliers in the Q-Q plot indicate the presence of non-Gaussian behavior in the residuals.

- **NGP**

Figure 3.11: Graphical Analysis of the Residuals of the NGP Series



Source: generated by the student using Python

The residuals for the NGP show no autocorrelation, indicating a well-fitted mean structure. However, non-normality and heavy tails suggest potential outliers or volatility that the model doesn't capture as shown in **Figure 3.11**.

➢ **To confirm the results of the visual inspection, we applied the following statistical tests:**

Autocorrelation is the correlation of a signal or time series with a delayed version of itself. It measures how related current values are to past values at different time lags (Huitema & Laraway, 2006). One of the most important autocorrelation tests is:

- **Ljung-Box Test:**
  - H_0: No autocorrelation in residuals.
  - H_1: Autocorrelation exists in residuals.

- **Durbin-Watson test:**
  - H_0: No autocorrelation in residuals
  - H_1: Autocorrelation exists in residuals

➢ If the p-value is greater than 0.05, we fail to reject the null hypothesis, indicating no autocorrelation in the residuals. Conversely, if the p-value is less than 0.05, we reject the null hypothesis, suggesting the presence of autocorrelation.

Normality: Refers to the assumption that data or residuals in a model follow a normal (Gaussian) distribution. This assumption is important for many statistical analyses to be valid (Ghasemi & Zahediasl, 2012). Common tests for normality include Shapiro-Wilk, Kolmogorov-Smirnov, and Jarque-Bera. These normality tests all share the same hypotheses:

- H_0: Data is normally distributed.
- H_1: Data is not normally distributed.

➢ If the p-value > 0.05, we fail to reject H_0 (normal distribution). If p-value < 0.05, we reject H_0 (non-normal distribution).

Heteroskedasticity : means the error sizes in a model vary instead of being constant (Godfrey, 2006; Stewart, 2005).

- **ARCH Test:**
  - H_0: Homoskedasticity (constant variance).
  - H_1: Heteroskedasticity (non-constant variance).

➢ If p-value > 0.05, we fail to reject H_0 (no heteroskedasticity). If p-value < 0.05, we reject H_0 (heteroskedasticity).

- **Breusch-Pagan Test:**
  - H_0: Constant variance (homoskedasticity).
  - H_1: Non-constant variance (heteroskedasticity).

➢ If p-value > 0.05, we fail to reject H_0 (homoskedasticity). If p-value < 0.05, we reject H_0 (heteroskedasticity).

Table 3.5: Stationarity Test Results on Residuals

	ADF	*PP*	*KPSS*
NFA	0.00	0.00	0.1
CIC	0.00	0.00	0.1
NGP	0.00	0.00	0.1

Source: generated by the student using Python

As shown in **Table 3.5,** the stationarity tests (ADF, PP, KPSS) applied to the NFA, CIC, and NGP series consistently indicate stationarity. Both the ADF and PP tests reject the null hypothesis of a unit root (p = 0.000), while the KPSS test does not reject the null hypothesis of stationarity (p = 0.1). Therefore, all three series can be considered stationary and used directly in time series models without further differencing.

- **Autocorrelation:**

The Ljung-Box test shows significant autocorrelation for NFA and CIC (p = 0.000), while NGP shows no significant autocorrelation across lags (p > 0.05) as shown in **Table 3.6**.

Table 3.6: Autocorrelation Test Results on Residuals

Lag	1	2	3	4	5	6	7	8	9	10
NFA	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
CIC	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
NGP	0.98	0.62	0.75	0.85	0.91	0.62	0.47	0.58	0.61	0.58

Source: generated by the student using Python

While the Durbin-Watson test was applied to check the residual behavior of the models, the results show a value of 1.72 for NFA, suggesting mild positive autocorrelation. CIC presents a lower value of 1.30, indicating significant autocorrelation that may impact model accuracy. In contrast, NGP records a value of 2.00, reflecting no autocorrelation and a stable model fit.

- **Normality**

The Shapiro-Wilk, Kolmogorov-Smirnov, and Jarque-Bera tests all indicate non-normality for NFA, CIC, and NGP (p = 0.0000), as shown in **Table 3.7**.

Table 3.7: Normality Test Results on Residuals

Normality Test	*Shapiro-Wilk*	*Kolmogorov-Smirnov*	*Jarque-Bera*
NFA	0.00	0.00	0.00
CIC	0.00	0.00	0.00
NGP	0.00	0.00	0.00

Source: generated by the student using Python

- **Heteroskedasticity**

The ARCH test indicates heteroskedasticity for NFA and CIC (p = 0), but not for NGP (p = 0.99). The Breusch-Pagan test shows no significant heteroskedasticity for any series (p > 0.05), as shown in **Table 3.8**.

Table 3.8: Heteroskedasticity Test Results on Residuals

P-Value	*ARCH Test*	*Breusch-Pagan*
NFA	0.00	0.06
CIC	0.00	0.08
NGP	0.99	0.09

Source: generated by the student using Python

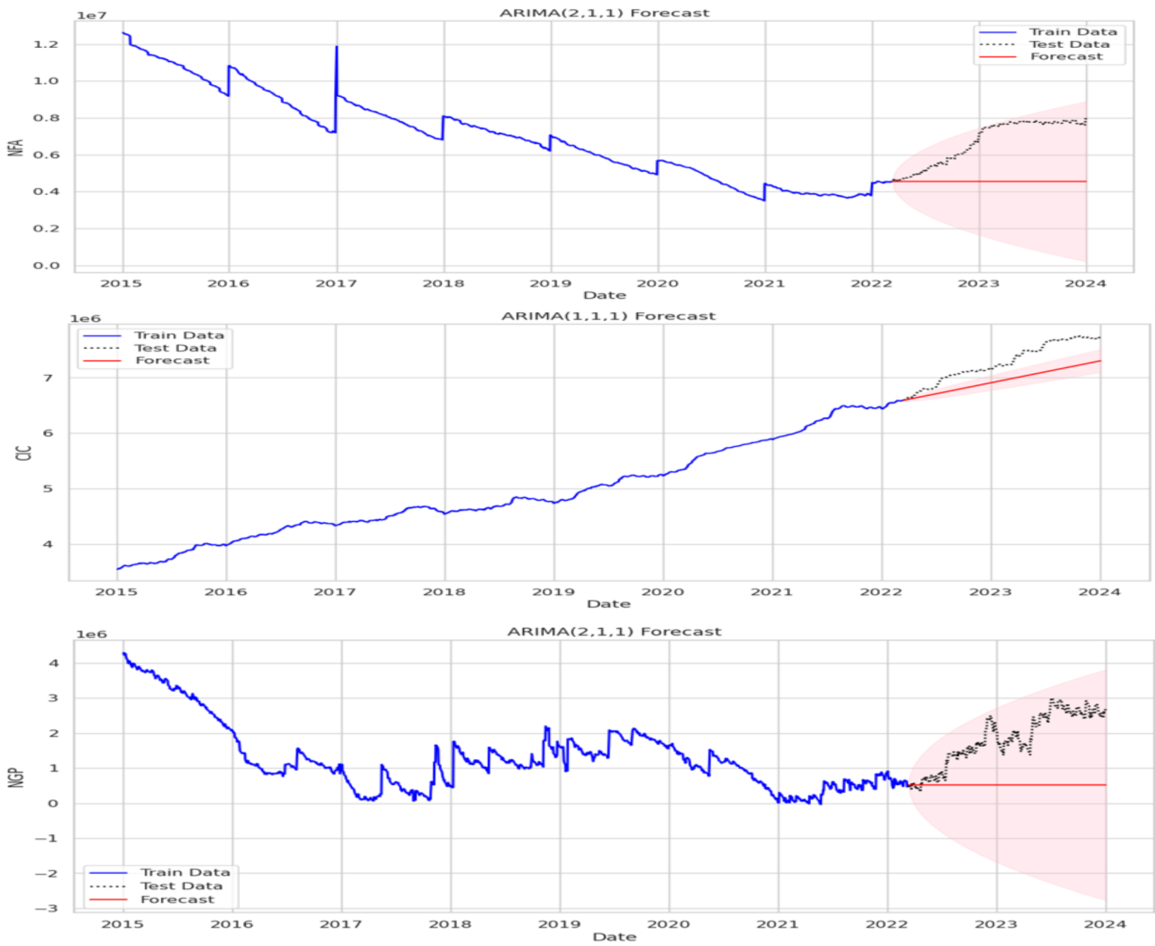
4.4. Forecast Results

We present the forecasting results of the VAR model, including both the all-at-once forecast and the Rolling Forecast.

4.4.1. By ARIMA all at once

After conducting all the required statistical tests and validating the stationarity and autocorrelation structure of our series, we proceeded with modeling using ARIMA models. We will forecast the data for the period from March 14, 2022, to December 31, 2023, as shown in **Figure 3.12**.

Figure 3.12: ARIMA Forecasting Results for the time Series at Once

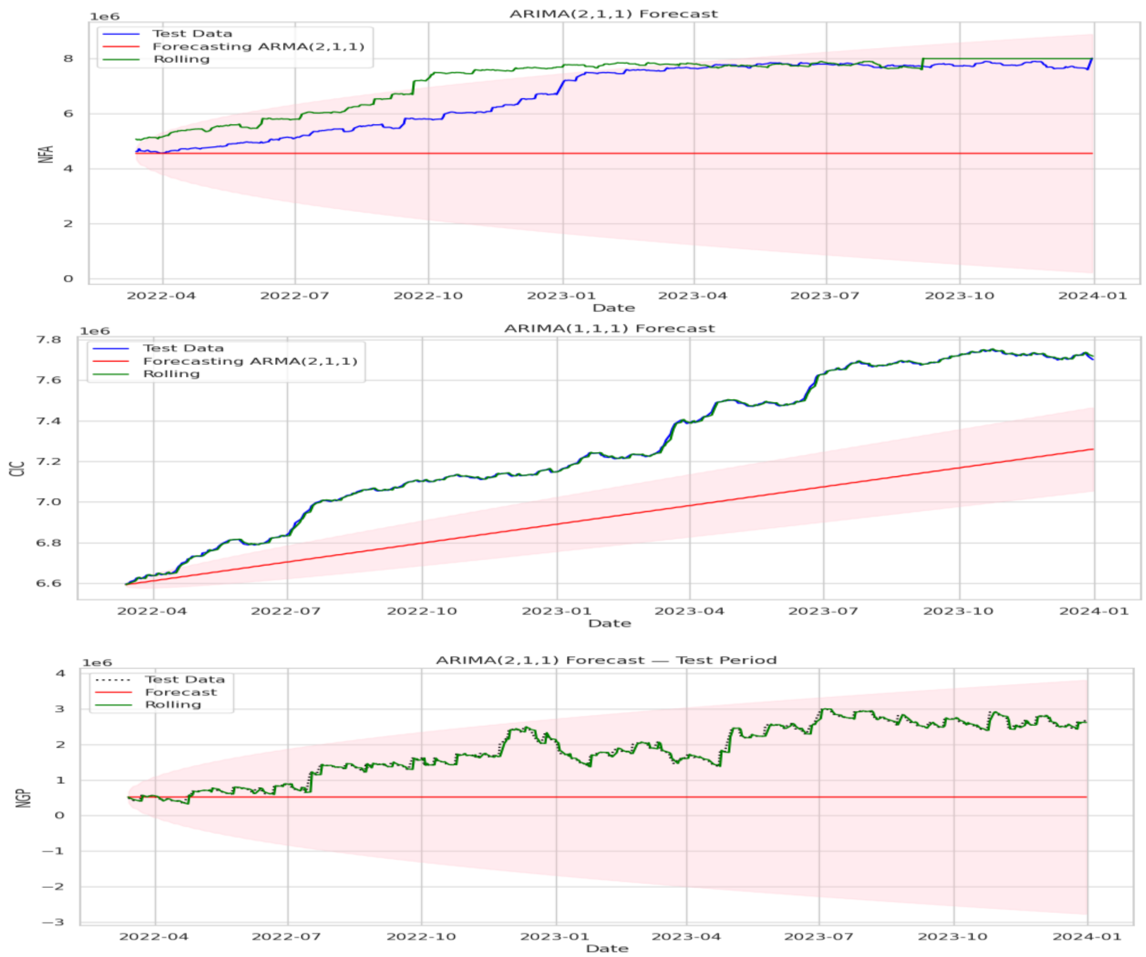


Source: generated by the student using Python

4.4.2. By ARIMA Rolling Forecast

Due to the limitations of the ARIMA model, we opted to use rolling forecasts to improve accuracy. A rolling forecast continuously updates future projections by replacing completed time intervals, offering ongoing insights and allowing for real-time adjustments (Optima Management Group, 2023). This approach enhances decision-making, supports strategic performance reviews, and improves expectation management. By providing up-to-date information, rolling forecasts help executives prepare for fluctuations, reducing the risk of unexpected profit warnings (Taoussi, Boudia, & Mazouni, 2024). As shown in the **Figure 3.13**, rolling forecasts demonstrate superior predictive performance over the ARIMA model.

Figure 3.13: ARIMA Rolling Forecast Results for three time series



Source: generated by the student using Python

5. Vector Autoregressive (VAR)

Vector Autoregressive is a group of time-series random variables is said to be generated by a Vector Autoregressive (VAR) model if each variable is expressed as a linear function of its own past values and the past values of the other variables in the system, along with an added random shock modeled as white noise (Eric Dor, 2004.).

Formally, a multivariate stochastic process X with n components is generated by a $VAR(p)$ model if there exists a vector μ, coefficient matrices Φ_i of dimension $n \times n$, and a multivariate stochastic process U, where each component of U is a white noise process, such that (Eric Dor, 2004):

$$X_t = \mu + \sum_{1=1}^{p} \phi_i X_{t-i} + U_t$$

- **General Representation of the VAR Model**

A Vector Autoregressive (VAR) process with N variables and p lags, denoted as VAR(p), can be written in matrix form as follows:

$$Y_t = \Phi_1 1Y_{t-1} + \Phi_2 1Y_{t-2} + \cdots + \Phi_P Y_{t-P} + u_t$$

where:

$$Y_t=\begin{pmatrix} Y_{1t} \\ \vdots \\ Y_{Nt} \end{pmatrix} \varepsilon_t = \begin{pmatrix} \varepsilon_{1t} \\ \vdots \\ \varepsilon_{Nt} \end{pmatrix} \Phi_0 = \begin{pmatrix} \alpha_1^0 \\ \vdots \\ \alpha_N^0 \end{pmatrix} \Phi_p = \begin{pmatrix} \alpha_{1p}^1 & \alpha_{1p}^2 & \cdots & \alpha_{1p}^N \\ \vdots & \vdots & \vdots & \vdots \\ \alpha_{Np}^1 & \alpha_{Np}^2 & \cdots & \alpha_{Np}^N \end{pmatrix}$$

where ε_t represents a white noise process with a variance-covariance matrix Σ. The equation can also be written as follows (Lardic & Mignon, 2006):

$$(I - \Phi_1 L + \Phi_2 L^2 + \cdots + \Phi_P L^p)X_t = \Phi_t + \varepsilon_t$$

5.1. VAR order selection

Before selecting the optimal lag length, the time series were transformed to ensure stationarity by applying appropriate differencing. We then used selection criteria such as AIC, BIC, FPE, and HQIC, which balance model fit and simplicity. While AIC and FPE suggest longer lags (e.g., lag 10), BIC, with its stricter penalty for complexity, recommends lag 5 as optimal. Given BIC's effectiveness in preventing overfitting, we chose lag 5 as the most suitable for our VAR model.

Equations for VAR Model (Lag 5):

$$\begin{pmatrix} \Delta\mathrm{NFA} \\ \Delta\mathrm{CIC} \\ \Delta\mathrm{NGP} \end{pmatrix} = \begin{pmatrix} -218.6001 \\ 636.7005 \\ -1234.8206 \end{pmatrix} +$$

$$\begin{pmatrix} 0.1574 & -0.7689 & 0.0042 \\ 0.0037 & 0.2925 & -0.0002 \\ 0.0084 & -1.1733 & 0.0087 \end{pmatrix} \begin{pmatrix} \Delta\mathrm{NFA}_t{}^{-1} \\ \Delta\mathrm{CIC}_t{}^{-1} \\ \Delta\mathrm{NGP}_t{}^{-1} \end{pmatrix} +$$

$$\begin{pmatrix} -0.1728 & -1.5996 & -0.0966 \\ 0.0018 & 0.1348 & -0.0012 \\ 0.0389 & -0.0457 & -0.0325 \end{pmatrix} \begin{pmatrix} \Delta\mathrm{NFA}_t{}^{-2} \\ \Delta\mathrm{CIC}_t{}^{-2} \\ \Delta\mathrm{NGP}_t{}^{-2} \end{pmatrix} +$$

$$\begin{pmatrix} -0.2131 & 0.1038 & -0.0237 \\ 0.0028 & 0.0706 & -0.0004 \\ -0.0141 & 0.5074 & 0.0237 \end{pmatrix} \begin{pmatrix} \Delta\mathrm{NFA}_t{}^{-3} \\ \Delta\mathrm{CIC}_t{}^{-3} \\ \Delta\mathrm{NGP}_t{}^{-3} \end{pmatrix} +$$

$$\begin{pmatrix} 0.0543 & -0.4996 & -0.0076 \\ 0.0019 & 0.0092 & -0.0003 \\ 0.0087 & 0.9582 & -0.0136 \end{pmatrix} \begin{pmatrix} \Delta\mathrm{NFA}_{t-4} \\ \Delta\mathrm{CIC}_{t-4} \\ \Delta\mathrm{NGP}_{t-4} \end{pmatrix} +$$

$$\begin{pmatrix} -0.0842 & -0.5551 & 0.1015 \\ 0.0020 & 0.2637 & -0.0004 \\ -0.0162 & -0.5513 & 0.0157 \end{pmatrix} \begin{pmatrix} \Delta\mathrm{NFA}_{t-5} \\ \Delta\mathrm{CIC}_{t-5} \\ \Delta\mathrm{NGP}_{t-5} \end{pmatrix} + \begin{pmatrix} \varepsilon_{(NFA,\mathrm{t})} \\ \varepsilon_{(CIC,\mathrm{t}} \\ \varepsilon_{(NGP,\mathrm{t})} \end{pmatrix}$$

5.2. Pearson Correlation Analysis

The Pearson correlation test quantifies the strength and direction of a linear association between two continuous variables through a correlation coefficient ranging from -1 (indicating perfect negative linear relationship) to +1 (indicating perfect positive linear relationship). The statistical significance of this correlation is evaluated using the p-value; a p-value less than 0.05

leads to rejection of the null hypothesis of no linear correlation, thereby supporting the presence of a statistically significant linear relationship (Field, 2013).

Hypotheses

- H0 (Null Hypothesis): There is no linear correlation between the two variables.
- H1 (Alternative Hypothesis): There is a significant linear correlation between the two variables.

As shown in **Table 3.9**, at lag 6, the p-values (all 0.0000) indicate that the correlations between AEN-PNG, AEN-CF, and PNG-CF are statistically significant.

Table 3.9: Results of Pearson Correlation Tests

Time series	*P-Value*
AEN-PNG	0.00
AEN-CF	0.00
PNG-CF	0.00

Source: generated by the student using Python

5.3. Granger causality test

Granger causality test in time series analysis, examines whether past values of one variable contain useful information for forecasting another variable. This test relies on hypothesis testing, where a p-value below the designated significance threshold results in rejection of the null hypothesis of no causality, indicating that the predictor variable Granger-causes the target variable in a predictive sense (Gujarati & Porter, 2009).

Hypotheses

- H0 (Null Hypothesis): Variable X does not Granger-cause variable Y (past values of X do not improve the prediction of Y).
- H1 (Alternative Hypothesis): Variable X Granger-causes variable Y (past values of X improve the prediction of Y).

As shown in **Table 3.10,** The Granger causality test shows that (CIC) significantly causes (NFA), while Gov (NGP) does not. NFA, however, causes NGP. There is no evidence that NFA causes CIC. A strong bidirectional relationship exists between CIC and NGP, indicating mutual influence. Overall, CIC appears to be a key driver in the system.

Table 3.10: Results of Granger Causality Tests Between Variables

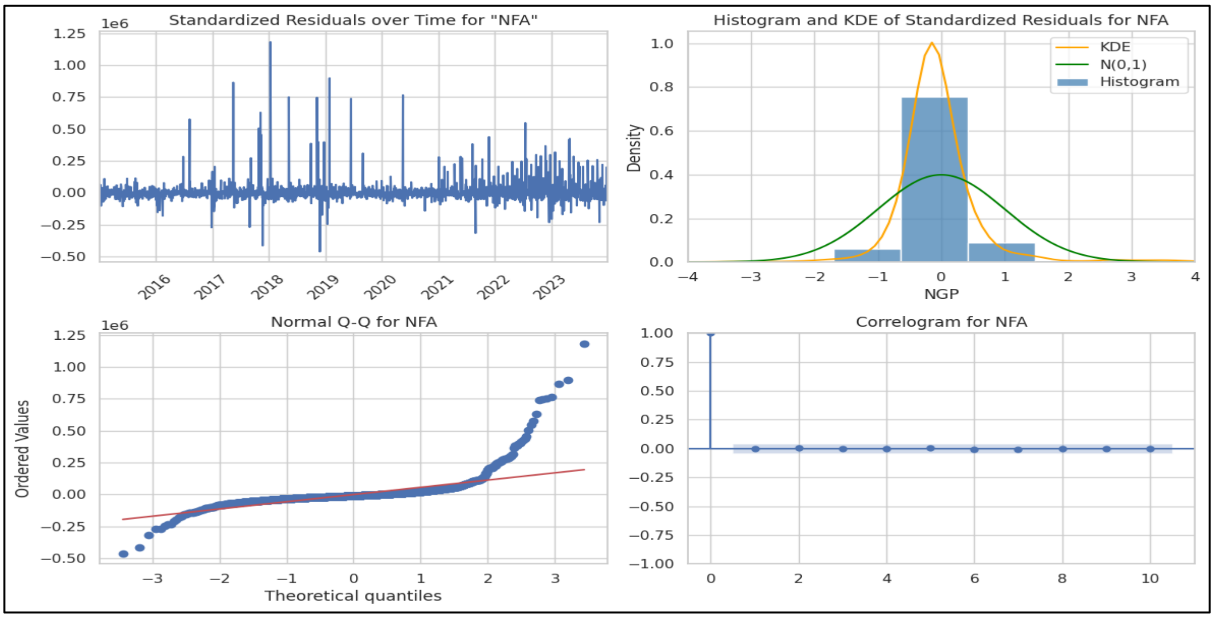
Time series	*NFA*	*CIC*	*NGP*
NFA	*-*	*0.0000*	*0.5063*
CIC	*0.0776*	*-*	*0.0000*
NGP	*0.0043*	*0.0073*	*-*

Source: generated by the student using Python

5.4. Residual diagnostics for NGP, NFA, and CIC

Figure 3.14 present the residuals for the (NFA) model show no significant autocorrelation across lags. However, slight deviations from normality and visible outliers in the Q-Q plot, along with heavier tails in the histogram, indicate non-Gaussian behavior in the residuals.

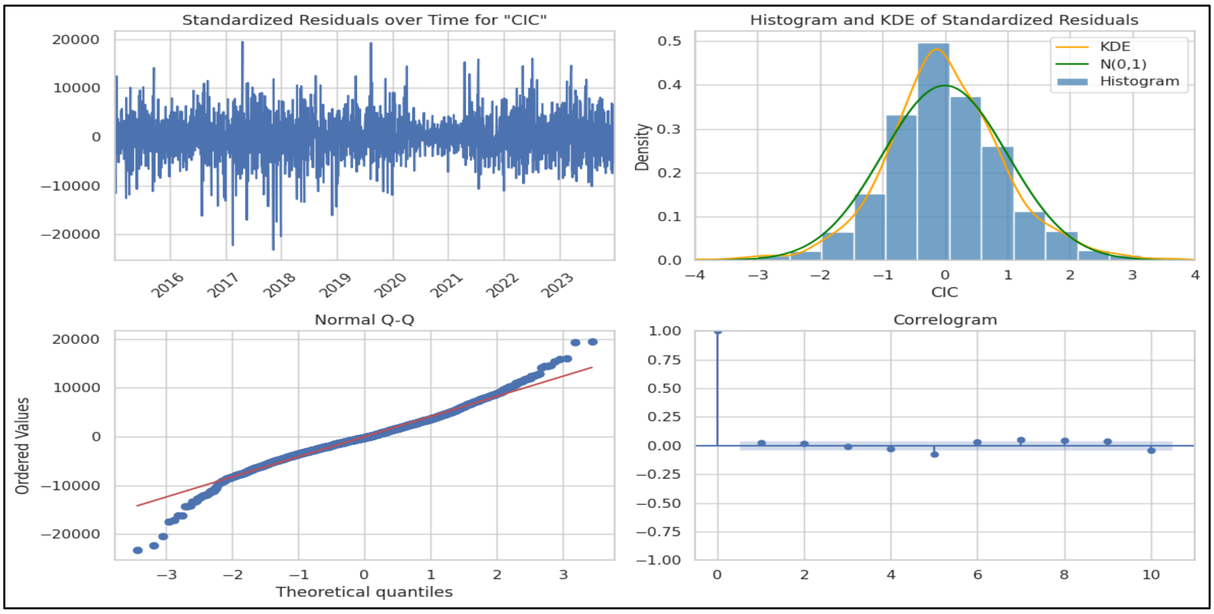
Figure 3.14: Residual diagnostics for NFA



Source: generated by the student using Python

The residuals for the (CIC) model show no significant autocorrelation across lags. However, slight deviations from normality and visible outliers in the Q-Q plot, along with heavier tails in the histogram, indicate non-Gaussian behavior in the residuals as shown in **Figure 3.15**.

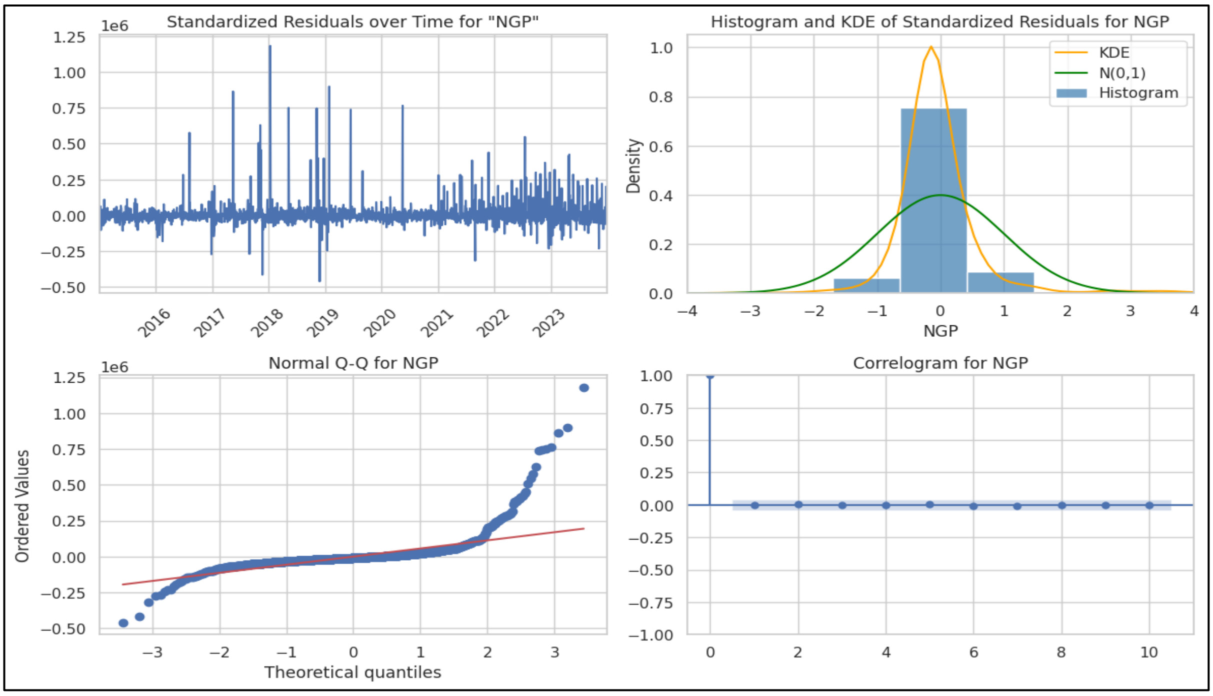
Figure 3.15: Residual diagnostics for CIC



Source: generated by the student using Python

The standardized residuals over time for Net Government Position (NGP) fluctuate around zero with noticeable spikes. The histogram and KDE reveal heavier tails than a normal distribution, while the Normal Q-Q plot shows deviations at the tails from normality. The correlogram indicates no significant autocorrelation as shown in **Figure 3.16**.

Figure 3.16: Residual diagnostics for NGP



Source: generated by the student using Python

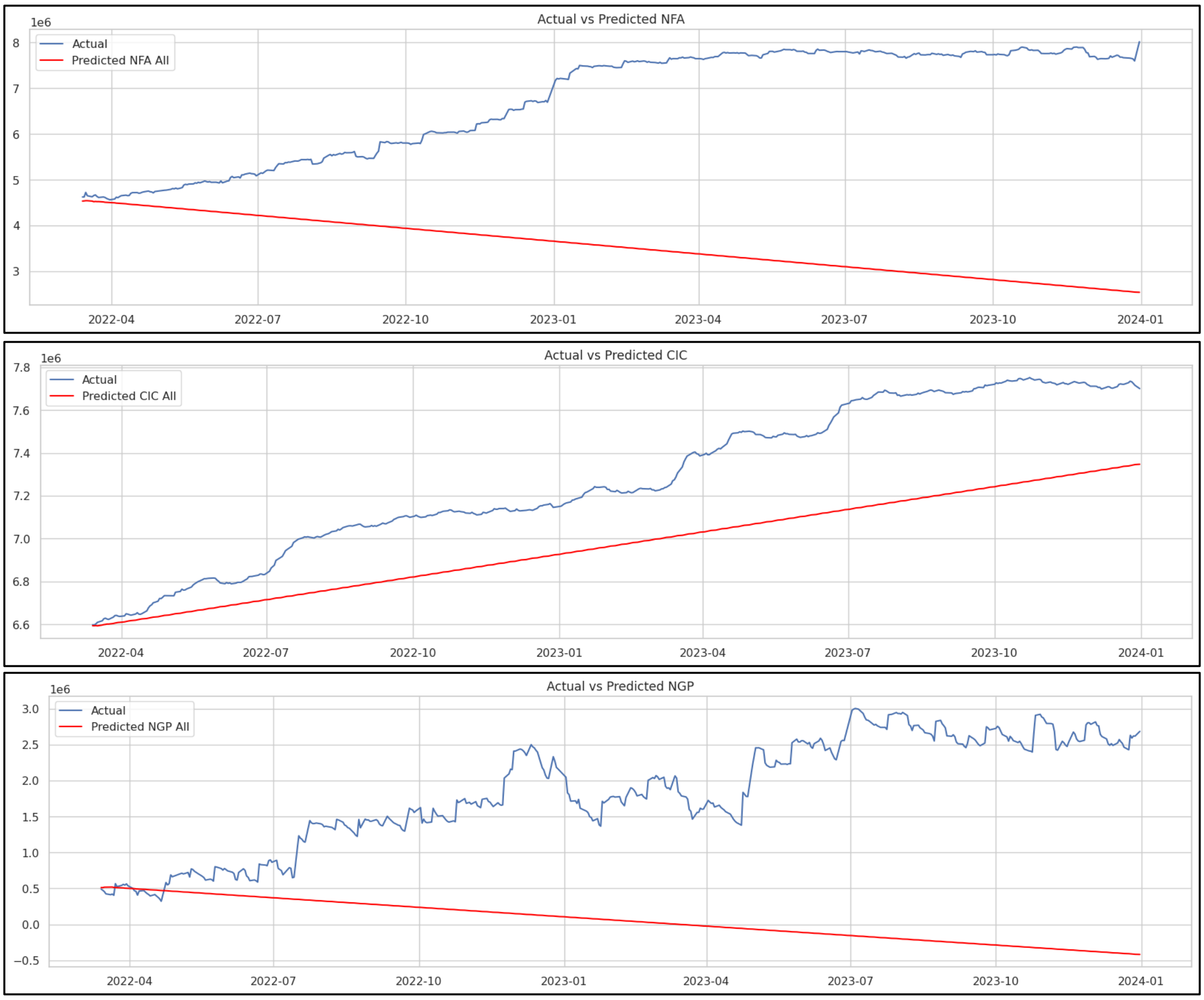
5.5. Forecast Results

we present the forecasting results of the VAR model, including both the all-at-once forecast and the Rolling Forecast.

5.5.1. VAR all at once

The VAR model was employed to forecast the evolution of Net Foreign Assets (NFA), Currency in Circulation (CIC), and Net Government Position (NGP) over the period March 14, 2022, to December 31, 2023, as shown in **Figure 3.17.**

Figure 3.17: VAR Forecasting Results for the Time Series at Once



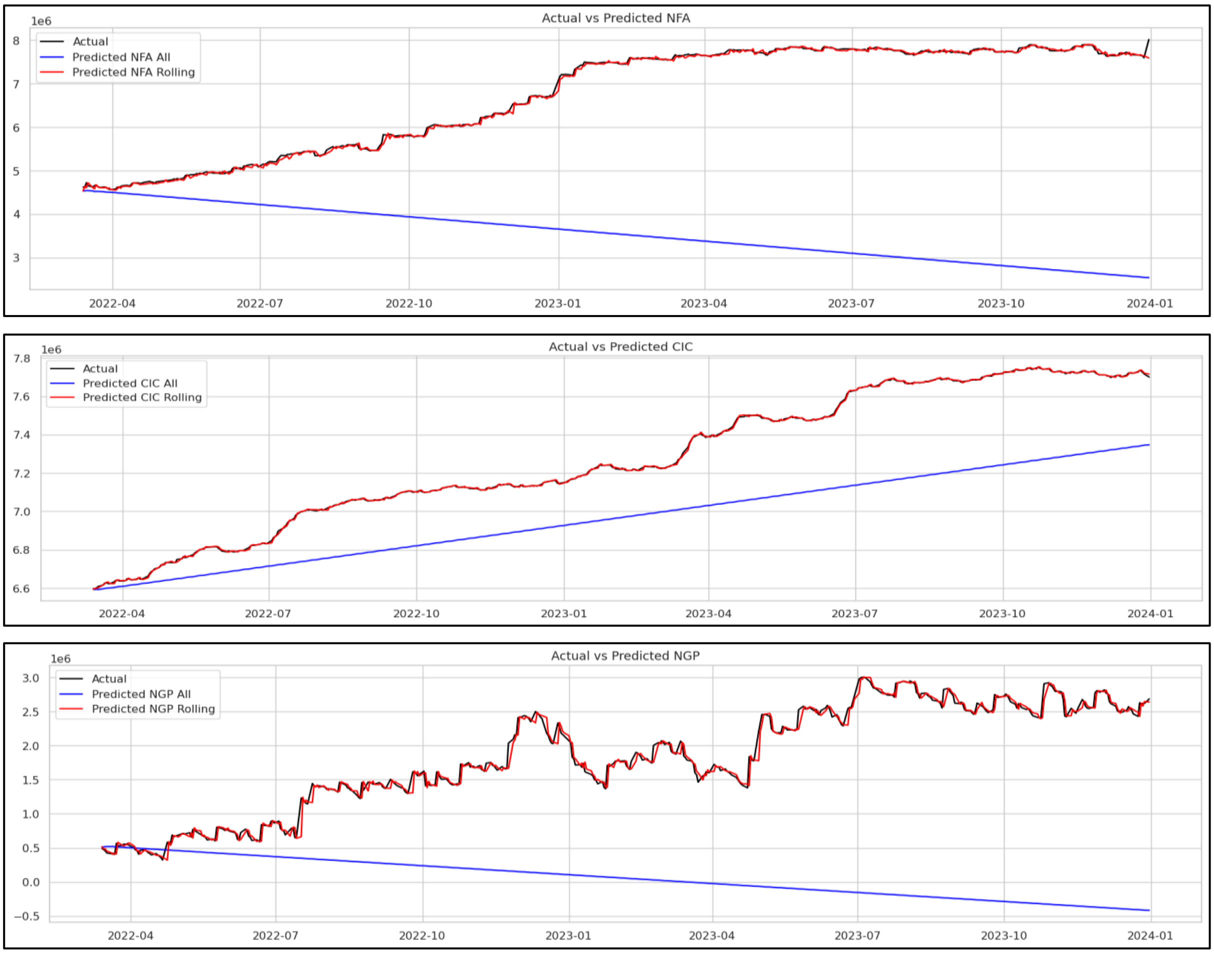
Source: generated by the student using Python

5.5.2. Rolling Forecasting

The initial forecasts generated by the VAR (Vector Autoregressive) model also exhibited poor performance, with notable discrepancies between the forecasted and actual values. To enhance the accuracy of the predictions, the rolling forecast technique was applied.

The results from the rolling forecast method, as shown in the **Figure 3.18**, indicate a significant improvement in the forecast accuracy over the initial VAR predictions.

Figure 3.18: Rolling Forecast of the three time series by VAR



Source: generated by the student using Python

6. Comparison Analysis

The comparison shows that the VAR rolling model consistently outperforms all others across NFA, CIC, and NGP, achieving the lowest RMSE, MAE, and MAPE. Rolling models (both ARIMA and VAR) perform much better than full-sample models, as they adapt to changing data. CIC is the easiest series to predict, while NGP is the most challenging, especially under ARIMA. Overall, using rolling estimation significantly improves forecasting accuracy

Table 3.11: Forecasting Accuracy of ARIMA and VAR Models

Unit: billion DZD

Time series	GoF	*ARIMA all at one*	*ARIMA Rolling Forecast*	*VAR all at once*	*VAR Rolling Forecast*
NFA	***RMSE***	2,460,390.11	678,930.14	3,608,526	46,733.27
	MAE	2,155 ,579.21	509,055.52	3,160,783.78	30,058.80
	MAPE (%)	29.67	8.66	43.56	0.47
CIC	***RMSE***	382,450.21	6,104.41	335,320.60	4,661.12
	MAE	46,142.60	4,691.81	305,882.61	3 ,658.45
	MAPE (%)	4.94	0.064	4.12	0.05
NGP	***RMSE***	1,511,650.81	86,939.3	2,041,501.98	85,431.87
	MAE	1,319,081.69	49,739.37	1,780,508.67	49,571.90.
	MAPE (%)	64.19	3.29	86.60	3.31

Source: generated by the student using Python

Section 3: Deep Learning Models

In this section, we apply deep learning models to forecast central bank liquidity. The goal is to compare the performance of different models on each time series in order to identify the most accurate one.

1. **Deep learning**

Traditional machine learning methods often require data to be carefully structured and features to be manually selected based on domain knowledge. While this approach can be effective, it limits the amount of data that can be used and requires significant expertise. In contrast, representation learning allows models to automatically learn the features and representations necessary for making accurate predictions, reducing the need for manual feature engineering.

One of the most powerful techniques in representation learning is deep learning. A deep learning model consists of multiple layers of interconnected neurons that process data in a hierarchical manner. Each layer extracts increasingly abstract features, starting from raw data in the input layer to complex representations in the output layer. The hierarchical processing of information allows deep learning models to excel at tasks like classification and regression, especially with high-dimensional data. (Samyak S Sarnayak , Abhijit Mohanty (2022))

1.1. Model structure

It defines how the layers are organized in the neural network. We have:

- **Input Layer:** This layer receives the input data and begins the process of information transmission through the network (Rajagukguk, Ramadhan, & Kim, 2020).
- **Hidden Layer:** The data is passed through one or more hidden layers, where features are extracted and patterns are learned (Rajagukguk, Ramadhan, & Kim, 2020).
- **Dense Layers:** it’s a particular case of a hidden layer, it’s a fully connected layer where each neuron is linked to every neuron in the previous layer.
- **Output Layer:** After processing through the hidden layers, the model generates predictions or classifications in the output layer (Rajagukguk, Ramadhan, & Kim, 2020).

The values from the input nodes (covariates) are multiplied by their respective weights (regression coefficients), and the resulting products are summed to produce the output.

1.2. Hyperparameters

They are predefined settings that guide how the model learns. We have:

- **Batch Size:** An important hyperparameter that determines the number of samples processed before updating the model's internal parameters (Boudart, 2022).

- **Epochs:** Refers to the total number of times the training algorithm processes the entire dataset.

1.3. Training the Neural Network

It involves feeding data to the model so it can learn patterns and make predictions. Key elements include:

- **Activation Function:** Each neuron receives a portion of the input and processes it through an activation function. Some commonly utilized activation functions include the sigmoid function, tanh, and ReLU. These functions are designed to normalize the output within a specific range, which helps the model achieve stable convergence during training (Boudart, 2022).

Table 3.12: Activation Functions Used in Neural Networks

Activation Function	*Formula*
Sigmoid	$\boldsymbol{\sigma(x) = \frac{1}{1 + e^{-x}}}$
Tanh	$\boldsymbol{tanh(x) = \frac{e^{x} - e^{-x}}{e^{x} + e^{-x}}}$
ReLU	***ReLU(x)=max(0,x)***

Source: Made by the student.

- **Weight Space:** Neurons are assigned numeric weights, which influence their output when combined with the activation function. The objective of training a deep learning model is to adjust these weights in such a way that the model produces the most accurate predictions possible (Boudart, 2022).

- **Initialization:** Before training begins, neural networks often use random initialization for the weights. This provides a starting point for the optimization process. One alternative approach, Xavier initialization, adjusts the weights to an optimal range to ensure that enough signal is passed through the layers, which helps improve the model's training (Boudart, 2022).

1.4. Loss Function

A cost function (or loss function) calculates the difference between the predicted value and the actual value, representing the error or loss in the model's predictions. Loss functions are essential in machine learning as they guide the model's training process by quantifying prediction errors, helping to adjust model parameters to minimize this error and improve accuracy (Boudart, 2022).

In regression tasks, common loss functions include (Terven et al., 2023):

- **Root Mean Squared Error (RMSE)**:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

MSE penalizes larger errors more heavily, making it more sensitive to outliers.

- **Mean Absolute Error (MAE):**

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|^{2^2}$$

- **Mean Absolute Percentage Error (MAPE):**

$$MAPE = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right|$$

The choice of a loss function depends on factors such as the type of problem, the data distribution, and the specific characteristics of the model. During training, optimization techniques like gradient descent are employed to minimize the loss function by iteratively adjusting model parameters, ultimately improving the model's accuracy.

1.5.Optimization and Learning

- **Gradient Descent:** is a technique used to adjust the parameters of a model by iteratively moving towards a lower value of a function. It does this by calculating the derivatives of the function with respect to each parameter, determining the optimal direction to minimize the function's value. By applying gradient descent to the error function, the model can refine its weights, reducing error and improving accuracy over time (Tapkir, 2023).

Training a neural network involves minimizing the loss function across the entire dataset. Ideally, this means computing the loss over all training samples. However, with thousands or even millions of data points, this approach is computationally expensive and can lead to memory overload (Tapkir, 2023).

To address this, two common solutions are used (Boudart, 2022):

- **Stochastic Gradient Descent (SGD):** The loss is evaluated and updated for each individual sample.

- **Mini-Batch Gradient Descent:** The loss is computed over small subsets (mini-batches) of data.

- **Backpropagation:** is a training algorithm used in artificial neural networks to minimize prediction errors by adjusting the connection weights between neurons. This iterative process continues until the network reaches an optimal level of accuracy (Crulis, Serres, de Runz, & Venturini, 2023), measured by a loss function.

The backpropagation process consists of two main phases:

- **Forward Propagation** – Data flows through the network from the input layer to the output layer. Each neuron computes its activation by applying an activation function to the weighted sum of its inputs, generating a final prediction.

- **Backward Propagation** – The error, calculated as the difference between the predicted and actual output, is propagated backward through the network. Using the chain rule, gradients of the loss function with respect to each weight are computed to adjust the model parameters, refining the predictions and optimizing the network.

- **Learning rate:** After calculating the gradients through backpropagation, the model parameters need to be updated. Adding the gradients directly could cause problems, as different data points may push the model in different directions, creating a rough path down the loss curve. To fix this, a learning rate is used to scale the gradients, making the descent smoother (Nawi et al., 2017).
- **Momentum:** The learning rate selected at the beginning of training might not remain effective later on. One way to address this issue is through using momentum (a widely used technique often applied alongside SGD). Momentum helps overcome obstacles during the optimization process. It accelerates when the gradient remains stable and reduces oscillations in narrow valleys of the loss function. This adjustment smooths the update process and allows the model to converge more efficiently (Sutskever, Martens, & Dahl, 2013).

2. Deep Learning Methods: LSTM and CNN Architectures

We will present the theoretical concepts of LSTM and CNN models used for time series forecasting.

2.1. Long Short-Term Memory networks (LSTM)

Recurrent Neural Networks (RNNs) are designed for processing sequential data by maintaining a memory of past inputs. They use feedback loops in hidden layers to retain temporal context. However, they struggle with learning long-term dependencies due to vanishing or exploding gradients.To overcome RNN's limitations, Hochreiter and Schmidhuber (1997) introduced the Long Short-Term Memory (LSTM) network. LSTM was specifically designed to solve the issues of vanishing and exploding gradients and improve long-term memory in sequence learning. The LSTM architecture is composed of cells that contain internal components known as gates (Ekundayo & Ezugwu, 2024):

- **Input Gate:** The input gate controls which parts of the incoming data are stored in the memory cell. It learns to activate when the input is relevant and deactivate when the input is not important.

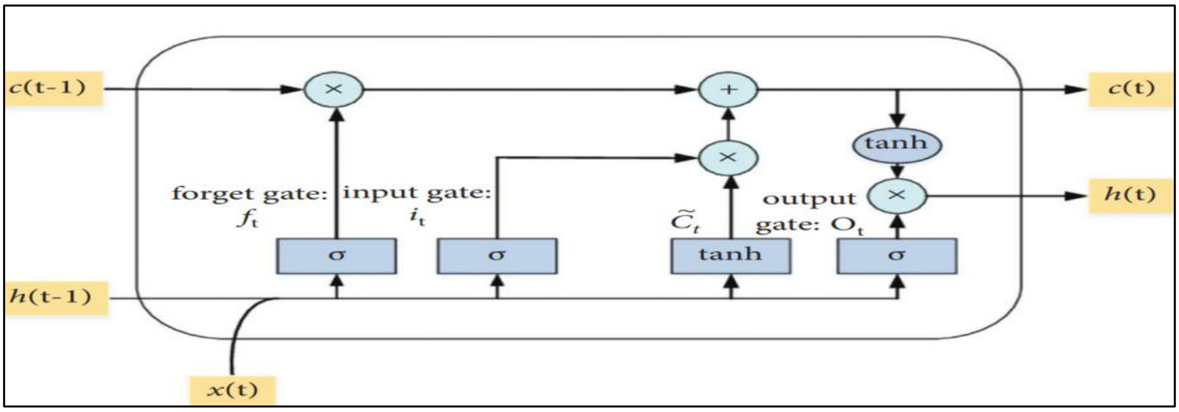
- **Forget Gate:** This gate decides what information from the memory cell should be discarded. It is trained to forget data that is no longer useful, helping the model focus on more relevant patterns over time.

- **Output Gate:** The output gate determines which parts of the memory should influence the output of the LSTM at the current time step. It opens for significant information and closes for irrelevant data.

These gates regulate the flow of information by deciding what to remember, what to forget, and what to output at each time step. Each LSTM cell takes in the current input, the previous hidden state, and the previous cell state, and it outputs an updated hidden state and cell state.

This gated structure enables LSTM to preserve long-term dependencies, making it more robust and stable for sequence prediction tasks than traditional RNNs. LSTM can pass relevant information across many time steps, avoiding the memory degradation seen in RNN.

Figure 3.19: Basic architecture of an LSTM used for time series prediction in a supervised model.



Source: Widiputra, H., Mailangkay, A., & Gautama, E. (2021).

2.2. Convolution Neural Network (CNN)

CNN is a non-linear model capable of autonomously extracting features from structured data such as images and videos (Dara & Tumma, 2018). Its architecture consists of multiple layers, including convolution, downsampling, activation functions, network optimization, and learning algorithms.

- **Input Layer:** Serves as the entry point for data, where the number of neurons corresponds to the number of input features. Preprocessing often enhances CNN performance.

- **Convolution Layer:** Applies filters to extract key features from input data. Activation functions like ReLU or Tanh introduce non-linearity, enhancing model efficiency (Ekundayo & Ezugwu, 2024).

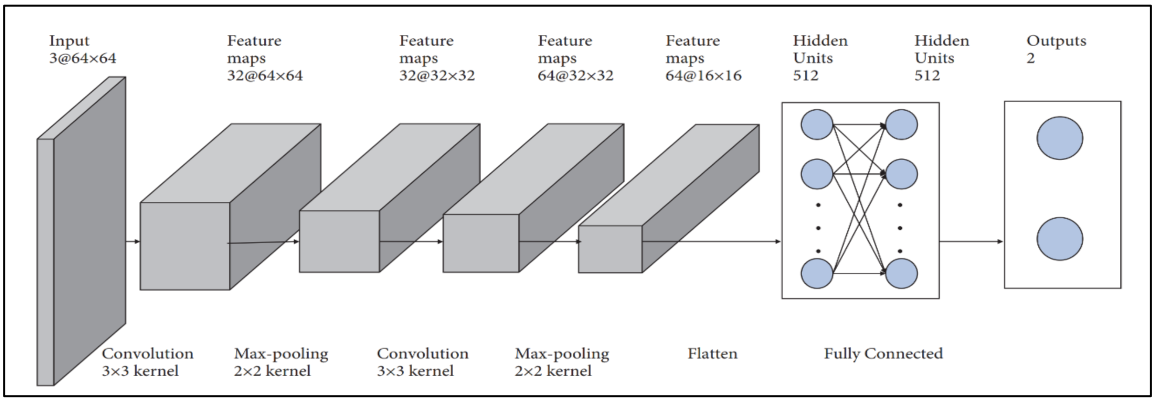
- **Pooling Layer:** Reduces dimensionality and computational complexity while preserving important features, using techniques such as max pooling or average pooling (Ekundayo & Ezugwu, 2024).

- **Fully Connected Layer:** Transforms extracted features into a final representation by connecting each neuron to the output layer (Ekundayo & Ezugwu, 2024).

- **Output Layer:** Uses classifiers like Softmax or Sigmoid to generate probabilities for classification tasks. Hybrid approaches may integrate traditional machine learning classifiers such as SVM or decision trees (Liang et al., 2021).

Although Convolutional Neural Networks (CNNs) are traditionally used with two-dimensional image inputs, their use is not limited to image processing. CNNs can also be adapted for predictive tasks involving other types of data. When dealing with one-dimensional inputs, there are generally two preprocessing strategies: one involves transforming the data into a two-dimensional format, while the other utilizes one-dimensional convolution operations directly.

Figure 3.20: The architecture of the CNN for the predictive model.



Source: Sim, H. S., Kim, H. I., & Ahn, J. J. (2019).

3. Application of the deep learning models

In this study, we apply LSTM and CNN architectures to the time series of central bank liquidity indicators. The forecasting process begins on March 14, 2022, with the goal of enhancing prediction accuracy by selecting the most appropriate architecture for each series.

To ensure a fair and consistent comparison, the same model architectures are applied uniformly across all time series. This methodological alignment allows for a reliable assessment of each architecture's strengths and limitations, making it possible to determine whether a particular architecture performs better overall or is more suited to specific data characteristics. The applied architectures are detailed in **Tables 3.13** and **3.14**.

Table 3.13: Selected LSTM Model Architecture

The hyperparameters	*LSTM unit*	*Activation function*	*optimizer*	*Loss function*	*Maximum Epochs*
LSTM 1	50	ReLU	ADAM	MSE	200
LSTM 2	64	Tanh	ADAM	MSE	200
LSTM 3	64	ReLU	ADAM	MSE	200

Source: Made by the student.

Table 3.14: Selected CNN Model Architectures

The hyperparameters	*Number of filters*	*Kernel*	*Activation function*	*optimizer*	*Number of units*	*Loss function*
CNN 1	32	3	ReLU	ADAM	32	MSE
CNN 2	64	6	Tanh	ADAM	32	MSE
CNN3	128	8	ReLU	ADAM	32	MSE

Source: Made by the student.

3.1. Net Foreign Assets (NFA)

We apply deep learning models, specifically LSTM and CNN, to the Net Foreign Assets (NFA) time series to evaluate their forecasting performance.

3.1.1. LSTM

According to the **Table 3.15,** Model 2 performs best with the lowest errors (MAE, MAPE, RMSE), indicating the most accurate forecasts. Model 1 is second, and Model 3 has the highest errors, making it the least accurate.

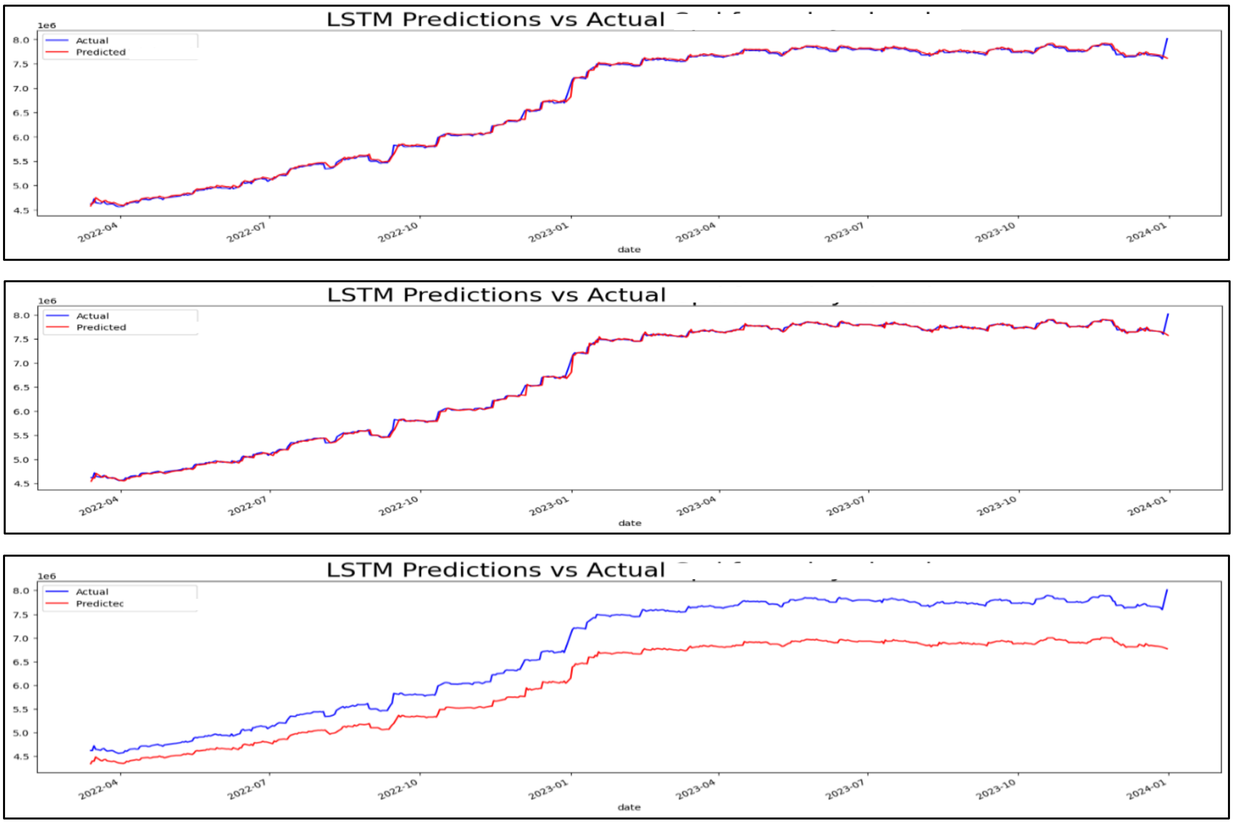
Table 3.15: Comparison of prediction error metrics for -LSTM-Models on NFA

GoF	*LSTM 1*	*LSTM 2*	*LSTM 3*
MAE	28893.75	23261.33	651093.63
MAPE (%)	0.44	0.35	9.32
RMSE	41722.85	40980.49	694192.87

Source: Made by the student.

Figure 3.21 shows the forecasting results of (NFA) for the three models respectively. We can visually confirm the results, as Model 2 captures the fluctuations better than the other two.

Figure 3.21: Performance overview of -LSTM- forecasting models on NFA



Source: generated by the student using Python

3.1.2. CNN

Table 3.16, presents the forecasting performance of three CNN-based models evaluated. Model 2 demonstrates the best predictive accuracy, with consistently lower errors across all metrics. Model 1 shows moderate performance, while Model 3 has the highest error rates, indicating less reliable forecasts. These findings suggest that Model 2 is the most effective CNN configuration for forecasting the central bank liquidity series.

Table 3.16: Comparison of prediction error metrics for-CNN-models on NFA

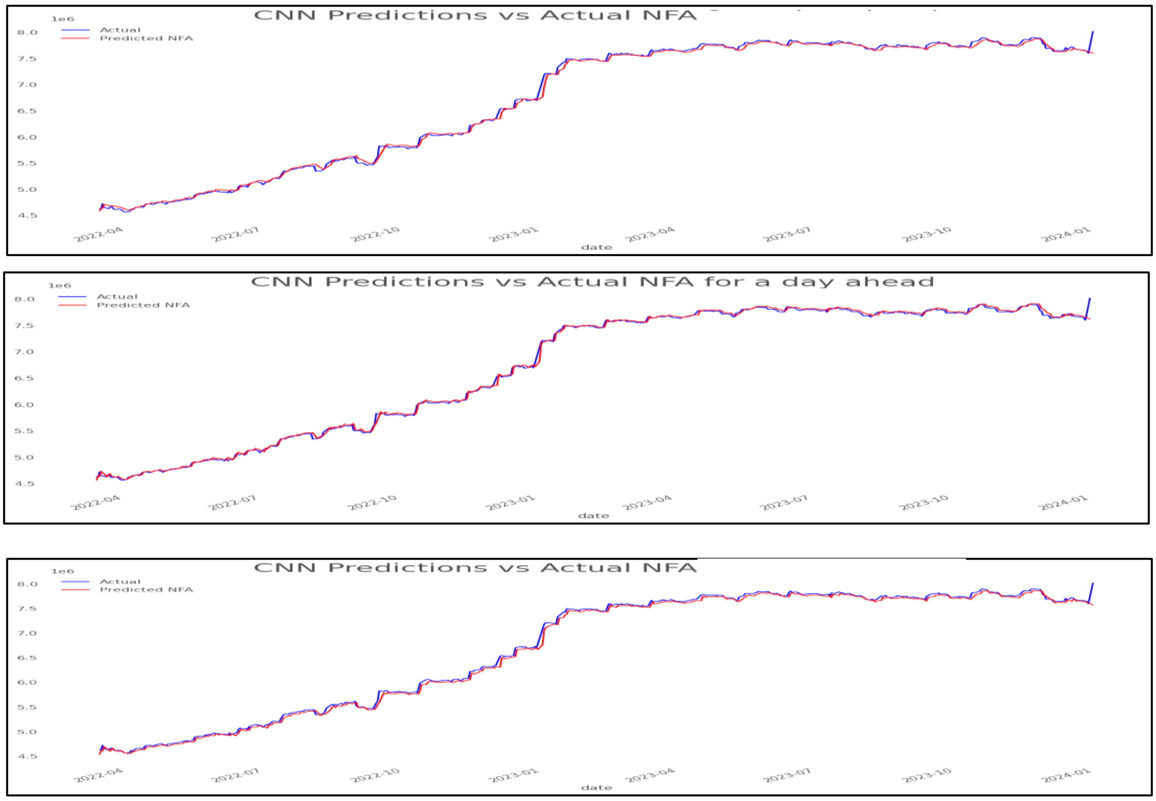
Unit: billion DZD

GoF	***CNN 1***	***CNN 2***	***CNN 3***
MAE	30739.97	26689.68	36703.64
MAPE (%)	0.47	0.40	0.56
RMSE	47750.04	40298.44	52500.66

Source: Made by the student.

Visually, Model 2 shows the best performance for NFA, closely following actual values with minimal deviation. Model 1 also tracks well but shows slightly more variation during flat periods. Model 3 performs similarly to Model 1 but appears slightly less aligned in some sections. Overall, Model 1 is the most accurate and stable visually. The results are shown in **Figure 3.22** of Model 1.2.3, respectively:

Figure 3.22: Performance overview of -CNN- forecasting models on NFA:



Source: generated by the student using Python

3.2. Currency in Circulation (CIC)

This part focuses on the application of LSTM and CNN models to the Currency in Circulation (CIC) time series in order to assess their predictive capabilities.

3.2.1. LSTM

Table 3.17 compares the performance of three models based on MAE, MAPE, and RMSE. Model 3 achieves the lowest errors across all metrics, indicating the highest accuracy and reliability. Model 2 performs slightly worse but still shows strong predictive capability. Model 1 has the highest error values, making it the least accurate. Overall, Model 3 is the best performer, followed closely by Model 2.

Table 3.17: Comparison of prediction error metrics for -LSTM-Models on CIC

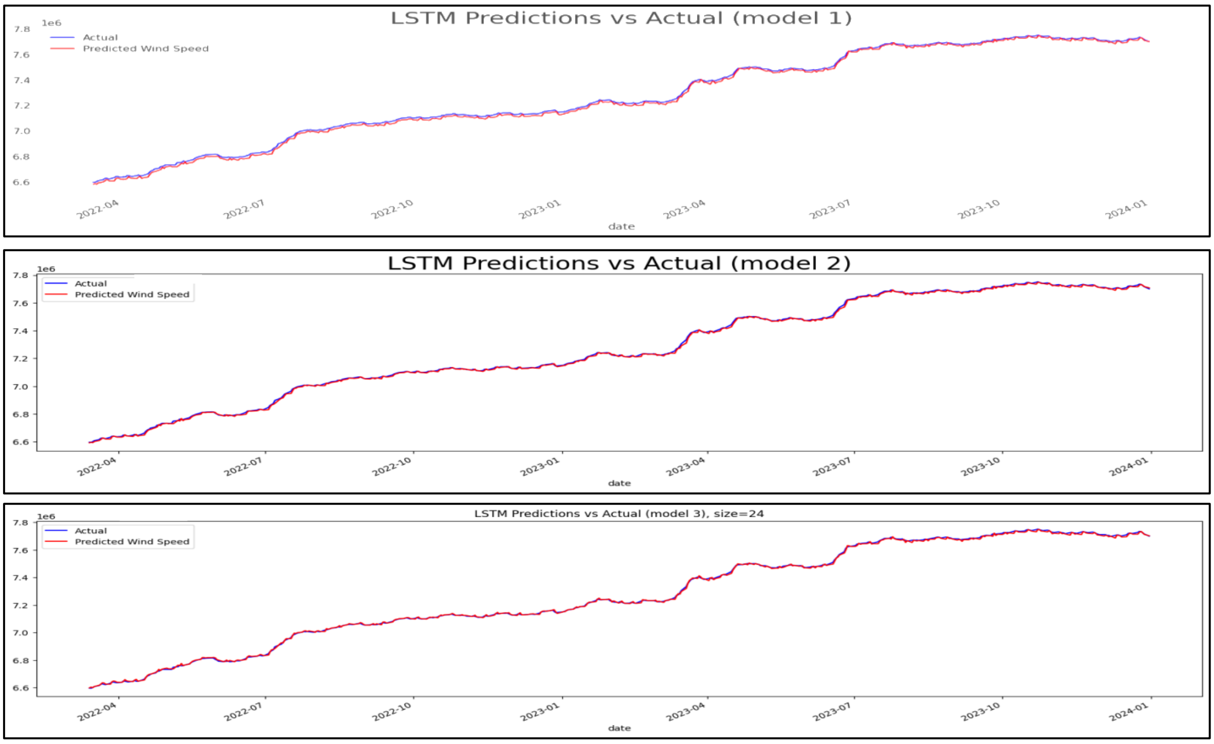
Unit: billion DZD

GoF	***LSTM 1***	***LSTM 2***	***LSTM 3***
MAE	13056.61	5480.36	5143.71
MAPE (%)	0.18	0.0753	0.0705
RMSE	14496.25	6958.94	6512.69

Source: Made by the student.

Figure 3.23 compares LSTM predictions to actual CIC values. Model 1 shows clear discrepancies, while Models 2 and 3 closely match the actual data. Model 3's smoother curve suggests better performance from refined tuning..

Figure 3.23: Performance overview of - LSTM- forecasting models on CIC



Source: generated by the student using Python

3.2.2. CNN

Table 3.18 compares the performance of three models using MAE, MAPE, and RMSE. Model 1 performs the best with the lowest errors, showing high accuracy and stability. Model 2 has the highest errors and is the least reliable. Model 3 offers moderate performance.

Table 3.18: Comparison of prediction error metrics for -CNN-Models on CIC

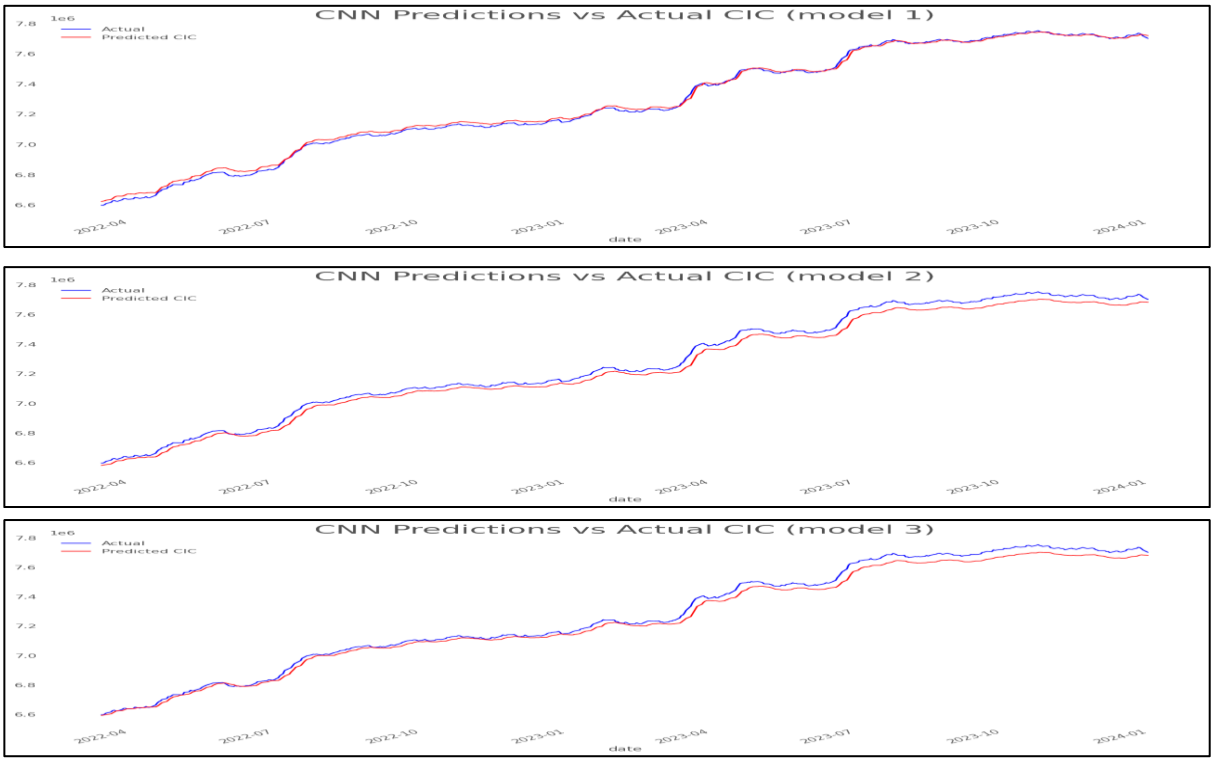
Unit: billion DZD

GoF	*CNN 1*	*CNN 2*	*CNN 3*
MAE	13476.86	33899.61	27386.46
MAPE (%)	0.18	0.46	0.36
RMSE	16254.23	36945.37	32726.89

Source: Made by the student

Visually, Model 1 is the most accurate, closely tracking actual CIC. Model 3 performs well but smooths some changes, while Model 2 lags and underestimates. This supports your MAE, MAPE, and RMSE results,as shown in **Figure 3.24**.

Figure 3.24: Performance overview of -CNN- forecasting models on CIC



Source: generated by the student using Python

3.3. Net Government Position

We implement LSTM and CNN models on the Government Net Position (GNP) time series to analyze their effectiveness in forecasting liquidity-related variables.

3.3.1. LSTM

The NGP-LSTM model shows the best performance in the third period across most metrics. The second period records the weakest results, while the first period demonstrates moderate performance overall as shown in **Table 3.19**.

Table 3.19: Comparison of prediction error metrics for -LSTM-models on NGP

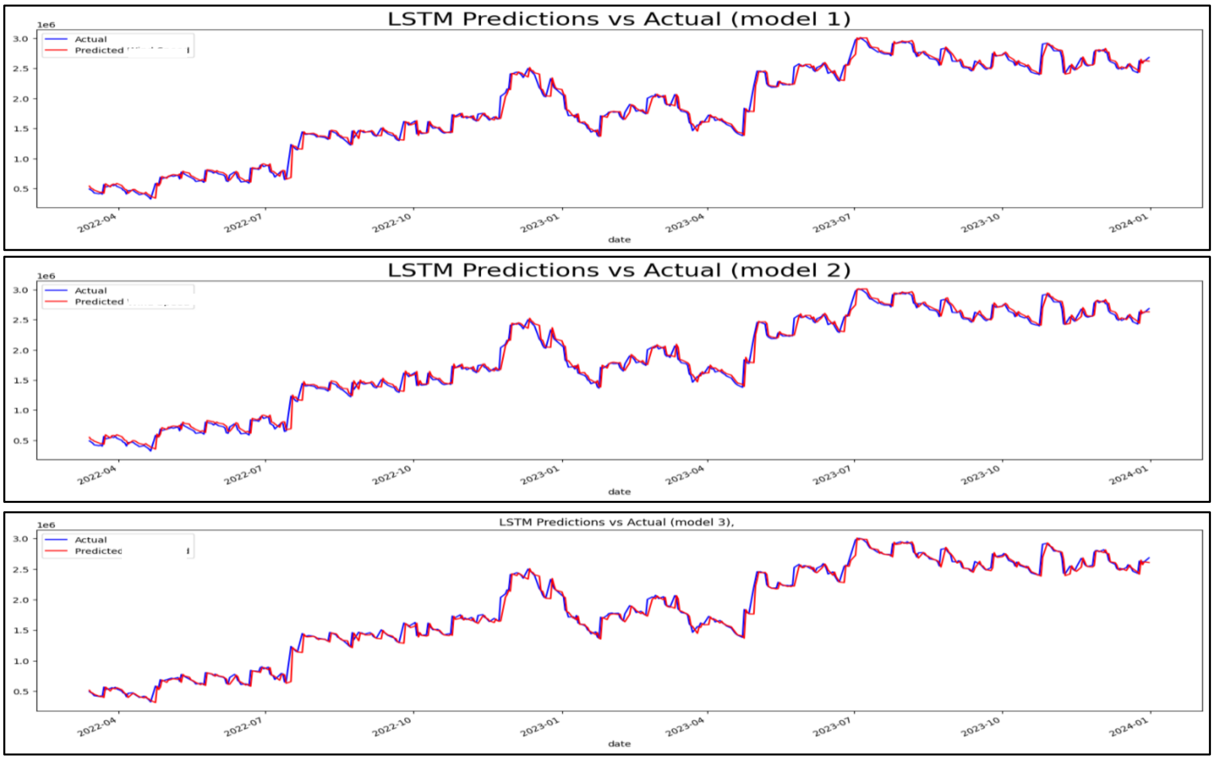
Unit: billion DZD

GoF	*LSTM 1*	*LSTM 2*	*LSTM 3*
MAE	*53040.98*	*57527*	*46678.45*
MAPE (%)	*3.64*	*4.08*	*3.05*
RMSE	*6717.39*	*87460.03*	*87888.63*

Source: Made by the student

The three models closely follow the actual data. Model 3 shows the best visual alignment, followed by Model 2, while Model 1 has slightly more deviation like the **Figure 3.25** present and that confirm the result:

Figure 3.25:Performance overview of LSTM- forecasting models on NGP



Source: generated by the student using Python

3.3.2. CNN

Table 3.20 compares the performance of three models for the NGP task using MAE, MAPE, and RMSE. Model 2 performs the worst across all metrics, indicating poor accuracy. Model 3 shows the best relative accuracy, while Model 1 slightly outperforms it in handling larger errors. Overall, Model 3 offers the best balance, making it the most suitable choice, while Model 2 should be excluded.

Table 3.20: Comparison of prediction error metrics for -CNN-models on NGP

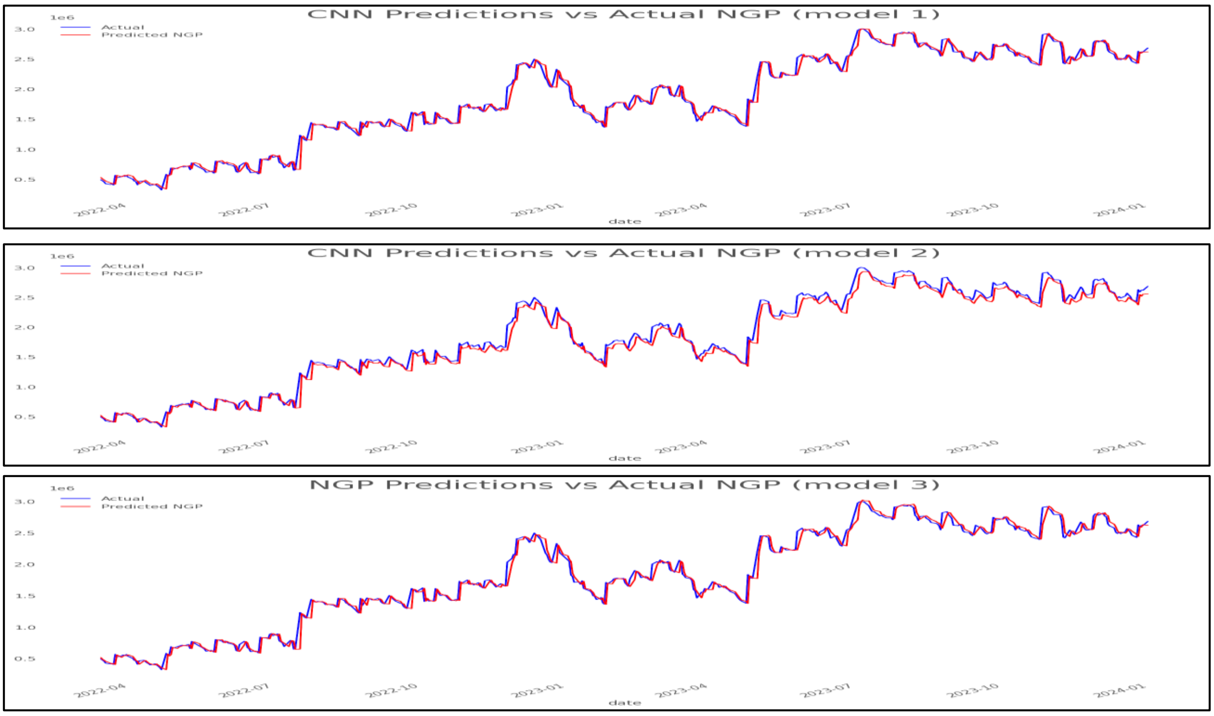
Unit: billion DZD

GoF	*CNN 1*	*CNN 2*	*CNN 3*
MAE	51540	63077.19	52581.79
MAPE (%)	3.47	3.80	3.35
RMSE	87050.74	101964.59	89249.94

Source: Made by the student

Visually, Model 3 shows the best alignment with actual NGP, closely tracking sharp peaks and drops. Model 1 also performs well with consistent tracking, though slightly less precise in volatile areas. Model 2 shows more noticeable deviations and lag during rapid changes. Overall, Model 3 appears the most accurate and responsive.The results are shown in **Figure 3.26** of Model 1.2.3, respectively:

Figure 3.26: Performance overview of -CNN- forecasting models on NGP



Source: generated by the student using Python

After comparison, we identified the best-performing LSTM and CNN models for each series. The results show that the LSTM model consistently outperformed the CNN model across all three series. **Table 3.21** presents the best model selected for each series.

Table 3.21: the best model selected for each time series

Time series	***NFA***	***CIC***	***NGP***
Best model	***LSTM (model 2)***	***LSTM (model 3)***	***LSTM (model 3)***

Source: Made by the student

Section 4: Comparison between Classical Time Series Models and Deep Learning Models

This section presents a comparative analysis between the best-performing classical time series model and the best deep learning model for each of the three economic indicators studied. By evaluating their forecasting accuracy using standard performance metrics, we aim to highlight the strengths and limitations of each approach. The comparison focuses on identifying which modeling technique, statistical or deep learning, offers better predictive performance and generalization across different types of time series.

1. Best Models: Statistical vs Deep Learning

Table 3.22 compares the performance of the VAR Rolling Forecast model and the LSTM model in predicting three economic variables: Net Foreign Assets (NFA), Currency in Circulation (CIC), and Net Government Position (NGP). For NFA, the LSTM model demonstrates superior accuracy across all evaluation metrics, highlighting its effectiveness in capturing complex and potentially nonlinear patterns. In contrast, the VAR model performs better in forecasting CIC, suggesting that this variable follows a more stable and linear trend, which aligns well with traditional time series models. Regarding NGP, the results are mixed: while the LSTM model yields lower average errors, the VAR model better manages large deviations. **Figure 3.27** presents the distribution of the forecasted liquidity levels, offering a visual representation of their frequency and dispersion.

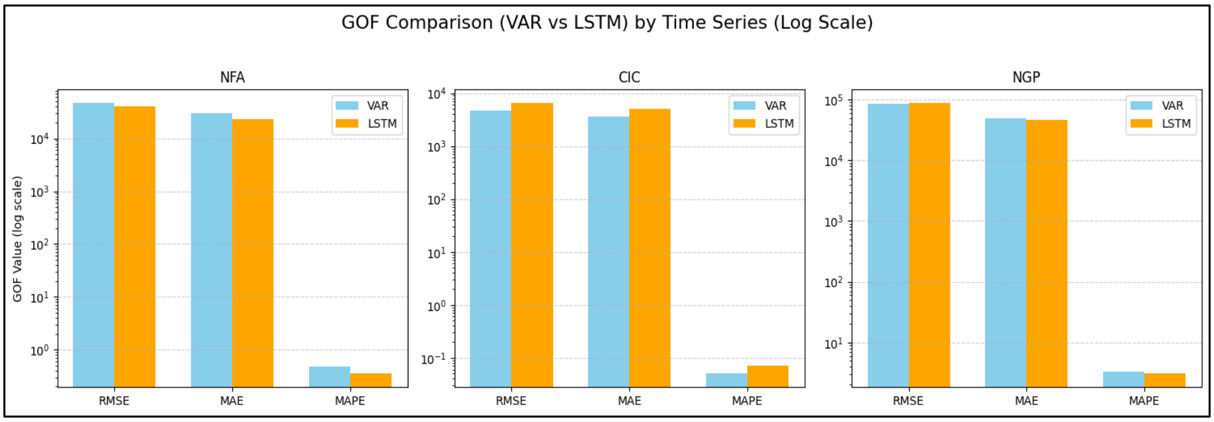
Table 3.22: VAR vs LSTM Forecast Comparison

Unit: billion DZD

Time series	GoF	*VAR Rolling Forecast*	*LSTM*
NFA	*RMSE*	46,733.27	40,980.49
	MAE	30,058.80	23,261.33
	MAPE (%)	0.47	0.35
CIC	*RMSE*	4661.12	6512.69
	MAE	3658.45	5143.71
	MAPE	0.05	0.07%
NGP	*RMSE*	85,431.87	87,888.63
	MAE	49,571.90	46,678.45
	MAPE (%)	3.31	3.05

Source: Made by the student.

Figure 3.27: Goodness-of-Fit Comparison by Time Series



Source: generated by the student using Python

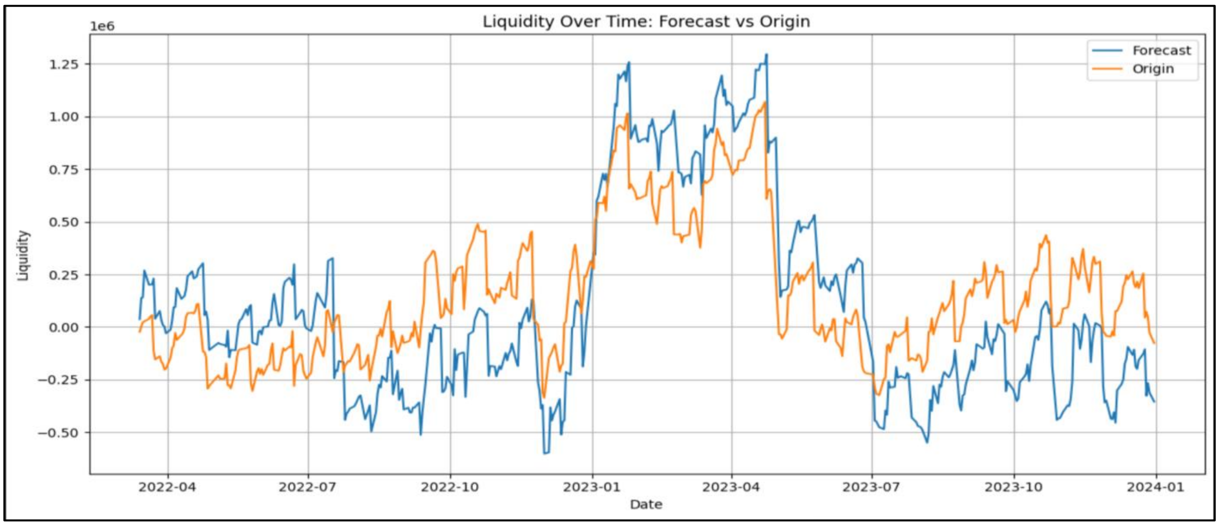
2. Forecasting Central Bank Liquidity

In the previous sections, we forecasted the Net Foreign Assets (NFA), Currency in Circulation (CIC), and Net Government Position (NGP) over 470 business day using the best models. We forecast the autonomous factors that influence central bank liquidity over a period of 470 days according to the forecasting equation:

Net autonomous factors = NFA – (CIC + NGP + Others)

The analysis is based solely on daily data of autonomous factors that affect central bank liquidity, enabling a detailed examination of their short-term impact on liquidity conditions. By focusing on daily observations, the forecasting models are better equipped to capture the day-to-day fluctuations of these factors, reflecting immediate changes that influence liquidity. These results are illustrated in **Figure 3.28**. The forecast model performs reasonably well in capturing major trends and peaks; however, it shows limitations in handling local variations and reducing errors during more stable periods

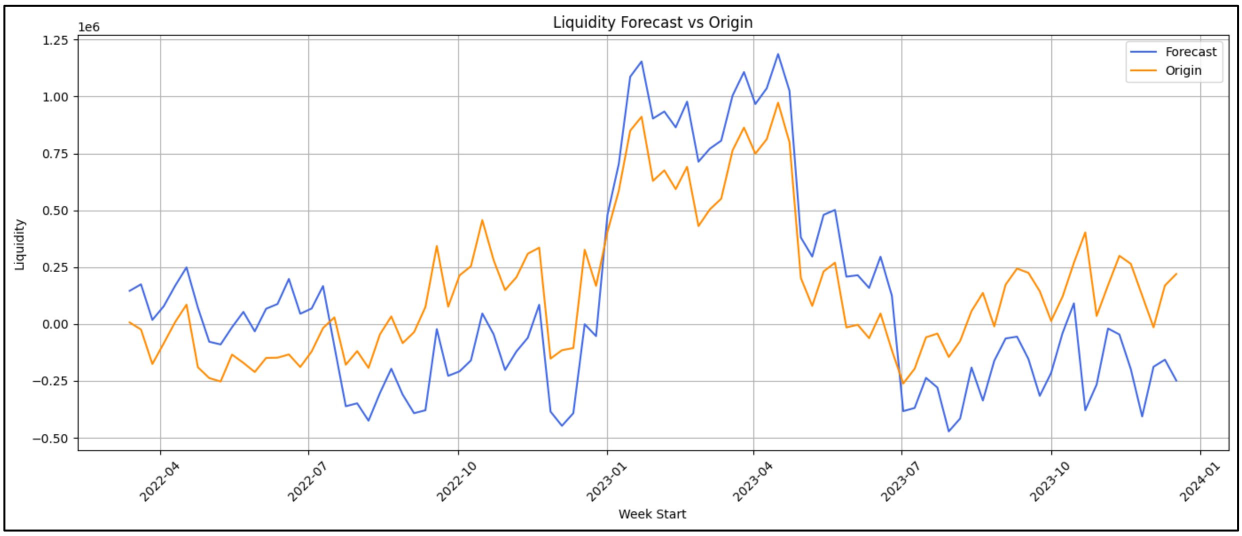
Figure 3.28: Daily Forecast of autonomous factors



Source: generated by the student using Python

Since the Bank of Algeria typically forecasts autonomous factors every week, we converted our business daily forecast data into weekly averages by calculating the mean over every five consecutive days (Sunday to Thursday), resulting in 94 business weeks (470 ÷ 5). These weekly forecasts align with the Bank's reporting frequency and are illustrated below, showcasing the model's performance over a weekly horizon. The weekly forecast captures the overall trend and seasonal patterns of the original data, including the sharp rise in early 2023, although some deviations appear in late 2022 and the second half of 2023. These deviations are reflected in the error metrics presented in **Table 3.23**, which quantify the differences between the forecasted and actual values.

Figure 3.29: Weekly Average Forecast of autonomous factors



Source: generated by the student using Python

Table 3.23: Weekly autonomous factors forecast accuracy metrics

Unit: billion DZD

GoF	***VALUES***
RMSE	283519.84
MAE	263275.78

Source: Made by the student.

Conclusion of the third chapter

This chapter focused on the application of both statistical and deep learning models to forecast the liquidity of the Bank of Algeria using three main indicators: Net Foreign Assets (NFA), Currency in Circulation (CIC), and Government Net Position (NGP). The models were applied to daily data covering the period from 2015 to 2023, allowing for a detailed and dynamic analysis of liquidity patterns.

We employed traditional statistical approaches, namely SARIMA and VAR, which are commonly used in time series forecasting due to their interpretability and effectiveness on stable data. In parallel, we implemented two deep learning architectures — Long Short-Term Memory (LSTM) and Convolutional Neural Networks (CNN) — known for their capacity to model nonlinearities and temporal dependencies in complex datasets.

The comparative analysis of model performance revealed distinct patterns depending on the nature of each time series. For relatively stable and regular series such as CIC and GNP, statistical models showed better performance, providing reliable forecasts with lower prediction errors. On the other hand, for more volatile and non-linear series like NFA, the deep learning models — particularly LSTM — delivered significantly improved predictive accuracy, capturing complex patterns that statistical models failed to represent adequately.

These findings underscore the importance of aligning model choice with the characteristics of the data. While statistical models remain valuable tools for stable economic indicators, deep learning models offer a powerful alternative for handling irregular or highly dynamic time series.

General Conclusion

This thesis aimed to explore the impact of deep learning models on the accuracy of bank liquidity forecasts in Algeria, with a particular focus on comparing these Deep Learning methods with traditional statistical models

The first chapter presented the theoretical framework of banking liquidity, focusing on key factors such as Net Foreign Assets, Currency in Circulation, and Government Net Position. These variables significantly influence liquidity levels, with NFA increasing liquidity and CIC and NGP reducing it. The chapter highlighted the interplay between internal banking policies and broader economic factors in liquidity management.

The second chapter focused on empirical studies of liquidity management and forecasting methods. We analyzed liquidity management to understand how banks respond to changes in liquidity factors. Additionally, we examined forecasting techniques essential for central banks to anticipate liquidity needs and guide monetary interventions. Although classical models like ARIMA and VAR are effective with limited data and linear trends, accurately forecasting liquidity remains challenging. Without reliable forecasts, central banks risk liquidity imbalances that could threaten financial stability. Therefore, developing advanced and precise predictive models is critical to enhance liquidity management, allowing proactive measures to support economic stability.

The third chapter was dedicated to the forecasting of the three main liquidity factors: Net Foreign Assets (NFA), Currency in Circulation (CIC), and Net Government Position (NGP), using both classical statistical models and deep learning approaches. The LSTM model consistently outperformed the CNN model, while the VAR model outperformed ARIMA. LSTM delivered more accurate forecasts for NFA and NGP, owing to its ability to capture complex and nonlinear dynamics. In contrast, the rolling forecast implementation of the VAR model yielded the best results for CIC, a variable characterized by relatively stable and less intricate behavior. The use of a rolling forecast allowed the VAR model to better adapt to structural changes over time, enhancing its predictive performance. These findings highlight that while deep learning models are more suitable for complex series, classical models can remain highly effective for simpler variables.

Our results show that Net Foreign Assets, Currency in Circulation, and Government Net Position are sufficient to forecast central bank liquidity. The models built on these variables provided reliable predictions, confirming their relevance without requiring additional factors. This supports the **hypothesis H1.**

Deep learning models, particularly LSTM, showed better performance than traditional methods in forecasting Net Foreign Assets (NFA) and Government Net Position (NGP). These models captured the patterns and variations in the data more effectively. Based on these results, **Hypothesis H2 is validated** for NFA and NGP, confirming that deep learning techniques are more suitable for forecasting these key components of banking liquidity in Algeria.

Deep learning techniques, particularly LSTM and CNN, tend to outperform statistical models like ARIMA and VAR when forecasting complex liquidity factors such as NFA and NGP. In contrast, VAR shows better performance with simpler and more stable variables like CIC. This suggests that statistical models are not always more effective, and that deep learning is better suited for capturing nonlinear and complex trends. Therefore, **Hypothesis H3 is validated**, as deep learning models are generally more appropriate for forecasting complex aspects of bank liquidity in Algeria.

This study provides contributions in three main axes: theoretical, methodological, and managerial.

On a theoretical level, this work presents significant contributions by deepening our understanding of liquidity and its key factors. It highlights the importance of accurately forecasting these liquidity components to enable effective liquidity management by central banks. Moreover, the study present the forecasting methods commonly used in central banking, to capture the dynamics of liquidity fluctuations. This theoretical foundation provides a comprehensive framework that supports the need for improved forecasting tools to enhance monetary policy decisions and financial stability.

Regarding the methodological aspect, this study applies a comprehensive approach to forecast the main factors of autonomous liquidity using both classical statistical models and deep learning techniques. This dual-method strategy allows a thorough comparison of model performances across different liquidity components. The methodology enhances the accuracy and robustness of liquidity forecasts, thereby supporting more effective liquidity management for the Bank of Algeria.

Finally, on the managerial level, this research emphasizes the importance of accurate liquidity forecasting for effective liquidity management by the Bank of Algeria. By identifying and validating key liquidity factors and comparing forecasting methods, the study provides valuable insights for central bank decision-makers. These insights can help optimize liquidity control strategies, improve monetary policy implementation, and ultimately contribute to maintaining financial stability in Algeria.

Despite the aforementioned contributions, it is important to acknowledge the limitations and challenges that may restrict the broader development and dissemination of this research. These limitations include:

- The models may require additional explanatory variables beyond the three liquidity factors studied to improve forecasting accuracy and capture other influences on central bank liquidity.
- The limited size and historical depth of the available dataset constrain the performance and generalization of both classical and deep learning forecasting models.

- The rapidly changing economic environment and structural shifts in the banking sector may affect the stability of model parameters over time, requiring continual model updating and validation.

For future research, it is recommended to include additional explanatory variables beyond the three liquidity factors examined, to improve the accuracy of forecasting models and better capture other influences on central bank liquidity. Increasing the size and historical depth of the dataset would also enhance the performance and generalizability of both classical and deep learning forecasting methods. Additionally, due to the rapidly evolving economic environment and structural changes in the banking sector, future studies should consider developing models that can be regularly updated and validated to maintain stable and reliable forecasts over time. These improvements would strengthen liquidity forecasting and support more effective liquidity management for the Bank of Algeria.

Based on the findings, we conclude that improving liquidity forecasting is essential for effective liquidity management at the Bank of Algeria. Accurate predictions help anticipate liquidity needs and support financial stability, highlighting the importance of continuously refining forecasting models to adapt to changing economic conditions

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Appendices

Appendix 1:Durbin-Watson test results for NFA

```
[ ] from statsmodels.stats.stattools import durbin_watson
    # Compute Durbin-Watson statistic
    dw_stat = durbin_watson(results_ARMA.resid[1:])
    print(f"Durbin-Watson statistic: {dw_stat:.2f}")

    Durbin-Watson statistic: 1.72
```

Appendix 2: Durbin-Watson test results for NGP

```
from statsmodels.stats.stattools import durbin_watson
# Compute Durbin-Watson statistic
dw_stat = durbin_watson(results_ARMA.resid[1:])
print(f"Durbin-Watson statistic: {dw_stat:.2f}")

Durbin-Watson statistic: 2.00
```

Appendix 3: Durbin-Watson test results for CIC

```
from statsmodels.stats.stattools import durbin_watson
# Compute Durbin-Watson statistic
dw_stat = durbin_watson(results_ARMA.resid[1:])
print(f"Durbin-Watson statistic: {dw_stat:.2f}")

Durbin-Watson statistic: 1.30
```

Appendix 4 : Stationarity tests before differencing

```
NFA
ADF Statistic: -2.7457073135997736
p-value: 0.0664573232295508

--------------------

NGP
ADF Statistic: -2.639968107720067
p-value: 0.08501477608361058

--------------------

CIC
ADF Statistic: 0.8999092130843989
p-value: 0.9930891414202183
```

Appendix 5: Stationarity tests after differencing

```
NFA
ADF Statistic: -23.587888490800943
p-value: 0.0

--------------------

NGP
ADF Statistic: -14.04514526661774
p-value: 3.2508023318531705e-26

--------------------

CIC
ADF Statistic: -7.886462074473021
p-value: 4.5558437909924980e-12
```

Appendix 6 : Optimal lag selection

```
 VAR Order Selection (* highlights the minimums)
==================================================
       AIC         BIC         FPE         HQIC
--------------------------------------------------
0        62.68       62.69   1.666e+27       62.68
1        62.52       62.56   1.423e+27       62.54
2        62.45       62.52   1.329e+27       62.48
3        62.42       62.50   1.279e+27       62.45
4        62.42       62.53   1.281e+27       62.46
5        62.34      62.48*   1.183e+27       62.39
6        62.32       62.48   1.157e+27      62.38*
7        62.32       62.51   1.158e+27       62.39
8        62.32       62.54   1.165e+27       62.40
9        62.31       62.56   1.153e+27       62.40
10      62.29*       62.56  1.125e+27*       62.39
--------------------------------------------------
```

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